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Modeling interactions among climate landscape and emerging diseases: A hantavirus case study

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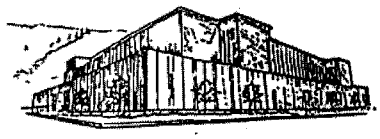

MODELING INTERACTIONS AMONG CLIMATE, LANDSCAPE, AND EMERGING DISEASES: A HANTAVIRUS CASE STUDY

by

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Modeling Interactions among Climate, Landscape, and Emerging Diseases: A Hantavirus Case Study

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Observed and predicted changes in global average temperature have significant impacts on ecosystem processes and functions. Such effects may be direct or indirect, and include melting of polar ice caps and glaciers, loss of valuable coastal areas associated with rising sea levels, changes in growing season length, northward shifts of temperature isoclines, increase in frequency of extreme weather events, and loss of important habitat areas for plants and animals. In addition, temperature and precipitation changes influence the global emergence and resurgence of vector-borne diseases, because these climatic variables affect the phenological development of disease agents and hosts and alter the geographic distributions of reservoir, host, and vector populations.

The sensitivity of *Peromyscus manicuatus* (deer mice) to fluctuations in temperature, precipitation, and resource abundance is important, as deer mice are the principal reservoir species and vector for Sin Nombre virus (SNV). This virus when transmitted to humans causes hantavirus pulmonary syndrome (HPS), an infectious disease with a high mortality rate. Trophic cascades are widely accepted as the catalyst for rodent population irruptions and emergence of HPS. Longitudinal rodent trapping data from study sites in Montana are used to evaluate associations between bioclimatology, resource abundance, sylvan and periodomestic *P. manicuatus* populations, and presence of SNV. Resource abundance is estimated using gross primary productivity (GPP) data from the Moderate Resolution Imaging Spectroradiometer (MODIS), a unique application of this satellite product. The MODIS GPP data provide a sensitive and highly accurate characterization of the land surface, and offer significant benefits over other satellite products for monitoring and modeling temporal and spatial variability in vegetation biomass.

An ecological footprint calculator, energy calculator, and resource mapping activity were developed for pre-college students. These tools provide a quantitative assessment of the anthropogenic contributions to global change, and facilitate understanding of the relationships between human consumption, ecosystem processes, and sustainability at multiple scales. This understanding is essential if we are to balance human needs against those of other organisms and the global ecosystem. Achieving this balance may be one mechanism for reducing the global disease burden and incidences of emerging disease outbreaks.

TABLE OF CONTENTS

ABSTRACT ii

ACKNOWLEDGEMENTS iii

TABLE OF CONTENTS iv

LIST OF TABLES vii

LIST OF FIGURES viii

EXECUTIVE SUMMARY x

CHAPTER 1 1

ABSTRACT 1

INTRODUCTION 2

PREDICTED HUMAN HEALTH HAZARDS 4

Malaria 5

Encephalitides 8

Rocky Mountain Spotted Fever 11

Hantavirus pulmonary syndrome 13

Bubonic plague 14

Waterborne diseases 15

Non-infectious health hazards 16

LARGE-SCALE CLIMATE TRENDS 18

METHODS 20

RESULTS AND DISCUSSION 22

Temperature 22

Precipitation 24

CONCLUSIONS 26

REFERENCES 30

CHAPTER 2 50

ABSTRACT 50

INTRODUCTION 51

Hantavirus ecology and epidemiology 51
Hantavirus modeling 54
Remote sensing 56
METHODS 57
Rodents 57
Bioclimatology 59
Remote sensing 61
RESULTS 65
Patterns in rodent abundance 65
Temporal correlations 66
Spatial correlations 68
DISCUSSION 68
CONCLUSIONS 72
REFERENCES 75
CHAPTER 3 92
ABSTRACT 92
INTRODUCTION 93
Modeling hantavirus risk 95
METHODS 101
Study sites 101
Vegetation abundance 102
Rodents 105
Statistical analysis 106
RESULTS AND DISCUSSION 106
Rodent density and seroprevalence 106
Gross primary productivity (GPP) 109
Linking vegetation abundance with disease risk 109
CONCLUSIONS 111
Suggestions for future research 112
REFERENCES 115

CHAPTER 4 ..... **130**
ABSTRACT 130
INTRODUCTION 131
WHAT IS ECOLOGICAL FOOTPRINT ANALYSIS? 134
IMPLEMENTING ECOLOGCAL FOOTPRINT ANALYSIS IN THE CLASSROOM 140
ECOLOGCAL FOOTPRINT ANALYSIS AND THE NATIONAL SCIENCE STANDARDS 145
CONCLUSIONS 146
RESOURCES FOR TEACHERS 149
GLOSSARY OF TERMS 150
REFERENCES 152
APPENDIX A 159
APPENDIX B 166

LIST OF TABLES

Table 1.1. Emergent and resurgent diseases and health hazards predicted for the northern Rocky Mountain region..... 38

Table 1.2. Site characteristics of meteorological stations used in the climate prediction scenario..... 39

Table 1.3a. Modeled annual temperature (°C) 39

Table 1.3b. Modeled seasonal temperature (°C)..... 40

Table 1.4. Modeled temperature change (°C) per 50 years..... 41

Table 1.5. Modeled precipitation (inches)..... 42

Table 1.6. Modeled precipitation change (inches) per 50 years..... 43

Table 2.1. Characteristics of rodent trapping grids including ground-reported (grid) land cover, UMD land cover class, and number of MODIS pixels used in the analysis..... 80

Table 2.2a. 2000-2003 within-site correlations in precipitation, GPP, and MNA..... 81

Table 2.2b. 2000-2004 within-site correlations in precipitation, GPP, and MNA..... 81

Table 2.3a. 2000-2003 between-site correlations in precipitation, GPP, and MNA..... 81

Table 2.3b. 2000-2004 between-site correlations in precipitation, GPP, and MNA..... 81

Table 3.1. Annual density and seroprevalence of sylvan and peridomestic rodents at trapping sites in west central Montana, January 1997-December 2004..... 121

Table 3.2. Pearson correlations between annual GPP, MNA, and MNI..... 121

Table 3.3. Spearman rank order and Pearson correlations between monthly GPP, MNA, and MNI..... 122

Table 4.1. Ecological footprints of nations in acres per capita..... 155

Table 4.2. Tie-ins between ecological footprint analysis and the National Science Education Content Standards..... 156

LIST OF FIGURES

Figure 1.1. Location of meteorological stations used in the climate prediction scenario..... 44

Figure 1.2. Average temperature change (°C) per 50 year period.... 45

Figures 1.3a and 1.3b. Observed (solid line) and predicted (dotted line) minimum annual temperature (a) and mean winter temperature (b) for Rock Springs, WY (1950-2000). 46

Figure 1.4. Average precipitation change (inches) per 50 year period..... 47

Figures 1.5a and 1.5b. Observed (solid line) and predicted (dotted line) total annual precipitation at Alta, WY (a) and Fortine, MT (b) (1950-2000)..... 48

Figures 1.6a and 1.6b. Observed (solid line) and predicted (dotted line) spring precipitation at Alta, WY (a) and Fortine, MT (b) (1950-2000)..... 49

Figure 2.1. Conceptual model of the relationships among precipitation, temperature, vegetation productivity, and rodent populations predicted under the trophic cascade hypothesis..... 82

Figure 2.2. Relationship between reservoir population density, probability of infection, and rate of disease transmission..... 83

Figure 2.3. HPS cases by state of residence, July 2005..... 83

Figure 2.4. Disease agent-host-environment interactions..... 84

Figure 2.5. Montana longitudinal rodent trapping sites included in the analysis, with UMD 1-kilometer land cover classes used in the MOD17 algorithm..... 84

Figure 2.6. Standard product MODIS data stream..... 85

Figure 2.7. Model components with data sources and variables. 86

Figure 2.8. Path diagram of potential within- and between-site correlations in precipitation, GPP, and rodent density..... 87

Figure 2.9. May-October *P. maniculatus* site total captures at the three Montana rodent trapping sites 87

Figure 2.10. 1994-2004 May-October *P. maniculatus* site average captures..... 88

Figure 2.11. Site average Minimum Number Alive (MNA) versus MODIS GPP, 2000-2003 and 2000-2004..... 89

Figure 2.12. Site average Minimum Number Alive (MNA) and MODIS GPP, 2000-2003 and 2000-2004..... 90

Figure 2.13. 2000-2004 site average Minimum Number Alive (MNA), MODIS GPP, and precipitation. 91

Figure 3.1. Observed trends in onset of HPS cases..... 123

Figure 3.2. Proposed relationships between rodent reservoir population parameters density, dispersal, and seroprevalence..... 123

Figure 3.3. Path diagram of proposed relationships between vegetation abundance (GPP) and sylvan and peridomestic *P. maniculatus* populations. 124

Figure 3.4. Study area showing location of peridomestic and sylvan study sites in west central Montana..... 125

Figure 3.5. Within-site, monthly comparison of sylvan and periodomestic population density and percent seroprevalance, 1997-2004..... 126

Figure 3.6. Within-site, annual comparison of sylvan and periodomestic population density and percent seroprevalance, 1997-2004..... 127

Figure 3.7. Between-site, monthly comparison of sylvan and peridomestic rodent density and percent seroprevalence, 2000-2004..... 128

Figure 3.8. Monthly MODIS GPP over sylvan and peridomestic study sites, 2000-2004, with sylvan and peridomestic rodent abundance..... 129

Figure 4.1. Actual (1950-2000) and projected (2000-2050) world population in billions of people..... 157

Figure 4.2. Ecological footprint 157

Figure 4.3 Ecological overshoot, 1961-2002..... 158

EXECUTIVE SUMMARY

My research focuses on the intersection of ecosystem ecology, epidemiology, and remote sensing science. Throughout my research I have approached the study of human epidemiology from an ecosystems perspective, attempting to discriminate the environmental and climatic factors that influence the emergence and distribution of pathogens, disease vectors, and susceptible populations. I have developed a unique approach to modeling and monitoring disease risk, which incorporates both intrinsic and extrinsic dynamics of disease agents and hosts. In contrast, traditional epidemiological approaches focus mainly on human dimensions of disease risk, especially demographics and activities associated with disease infection and transmission. The field of disease ecology primarily addresses intrinsic dynamics of populations that lead to establishment and maintenance of pathogens within reservoir populations. Traditional remote-sensing based ecosystem analysis often focuses on primary ecosystem responses to variations in abiotic and biotic parameters, rather than secondary effects of land cover change on organisms. Human alteration of ecosystems has resulted in rapid and global-scale changes in climate and land cover, which have been linked to the emergence and resurgence of a number of serious diseases. Through the research presented here I hope to contribute to those fields listed above, suggest new ways to integrate core ideas from each, and improve efforts to forecast and reduce human disease risk.

The progression of Chapters 1, 2, and 3 follows from (1) a general discussion of climate effects on diseases, providing evidence that changes in temperature and precipitation influence timing and magnitude of disease outbreaks; to (2) an analysis of the relationships among annual temperature, precipitation, and MODIS GPP, demonstrating that although there is some association among these variables, intra-annual dynamics may contribute significantly to reservoir responses to climate and landscape variability; to (3) analysis of intra-annual dynamics between landscape composition and sylvan and peridomestic reservoir population density and seroprevalance, the results of which indicate that MODIS

GPP can be used to predict reservoir population density on a monthly time scale. The fourth chapter in the dissertation presents a model for incorporating ecosystem processes and global change dynamics into environmental education. I developed three activities to teach these concepts to upper elementary and middle school students, and provided background material on global change, ecosystem processes, and ecological footprinting for teachers. Although this chapter does not directly relate to disease ecology or epidemiology, it addresses the need to define and limit those human activities that contribute to global atmospheric and terrestrial change, and have deleterious effects on ecosystems, organisms, resource quality and quantity, global sustainability, and the human disease burden.

Chapter 1

United States Historical Climatology Network (USHCN) temperature and precipitation data from twelve monitoring stations in Idaho, Montana, Wyoming were used to develop historic and predictive climate scenarios and assess the potential effects of climate change on human health in the northern Rocky Mountain region. The paper presents a method for evaluating regional climate variability that can be applied for any areas for which historical temperature and precipitation data are available. I also evaluate human health hazards that may emerge as the result of climate change. Particularly emphasized are arthropod-borne, rodent-borne, and waterborne diseases and non-infectious health hazards that are sensitive to variations in temperature and precipitation. Predicted regional climate changes include increased mean annual and mean spring and summer temperatures, asymmetrical increases in minimum annual temperature over maximum annual temperature, and increased total annual precipitation. Diseases that may emerge or increase in scope because of predicted climatic change include malaria, Saint Louis encephalitis, West Nile encephalitis, Rocky Mountain spotted fever, hantavirus pulmonary syndrome, plague, Cryptosporidiosis, giardiasis, heat stress, and respiratory disease.

Chapter 2

Relationships among rainfall, resource abundance, and *Peromyscus maniculatus* rodents are modeled using precipitation data from the National Climatic Data Center, vegetation gross primary productivity (GPP) from the Moderate Resolution Imaging Spectroradiometer (MODIS) and rodent population data from three longitudinal study sites in Montana. *P. maniculatus* (deer mice) are the main reservoir host for Sin Nombre virus (SNV), the primary disease agent of hantavirus pulmonary syndrome (HPS). *P. maniculatus* populations fluctuate widely, and increasing population density may significantly affect human risk of disease through increased probability of contact between humans and infected animals. Changes in weather and plant productivity have been noted as likely catalysts of population irruptions, and modeling of these phenomena may allow for development of early-warning systems for disease risk. Results from this study show that at an annual time scale MODIS GPP and rodent density were strongly correlated for 2000 through 2003. Data from 2004 fall as outliers in the distribution, weakening correlations across all study sites. Although annual-scale vegetation abundance and rodent population density are associated, other ecological processes likely play a dominant role in influencing rodent population variability. Such processes may include threshold effects of climate on reproduction and survival, competition, predation, or density-dependent population cycling, and are undetectable using the current framework. Intra-annual associations between model variables may also be influential in developing a best fitting model, and should be examined in future studies.

Chapter 3

Longitudinal rodent trapping data from sylvan (wild) and peridomestic (in close proximity to humans) sites in west central Montana were compared with vegetation productivity estimates from the Moderate Resolution Imaging Spectroradiometer (MODIS) remote sensor, to identify reservoir population and landscape characteristics associated with risk of hantavirus pulmonary syndrome (HPS) in human populations. Although almost all recorded HPS cases result

from peridomestic exposure to infected rodents, most studies focus only on dynamics of sylvan populations. Alternatively, the current study examines interactions between sylvan and peridomestic populations and the environment that contribute to development of large, infective disease reservoir populations, implicated in transmission of hantavirus to humans. From 1997 through 2004 overall reservoir population size was greater at the sylvan site, although peridomestic seroprevalence was markedly higher. At annual and monthly time scales rodent density at the sylvan site was significantly and positively correlated with peridomestic population density and seroprevalence, suggesting that dispersal between sylvan and peridomestic habitats may facilitate disease transmission between populations. Vegetation gross primary productivity was positively associated with sylvan rodent population density, suggesting that variability in deer mouse populations is partially driven by a trophic cascade response; however, MODIS GPP explained only 12% of the variability in population density, indicating that other factors influence reservoir population dynamics.

Chapter 4

Ecological footprint (EF) analysis calculates the energy and resource needs of a population in terms of the land and water area required to sustain that population (Wackernagel and Rees 1996, Ferguson 2002, Wackernagel et al. 2002). This paper provides background information on ecological footprinting, especially as it relates to environmental education; curriculum ideas for teaching about environmental sustainability and resource use; and a classroom tool for calculating students' ecological footprints. Humanity's use of Earth's resources is not fixed in space or time: resource needs vary within and among countries, and as our global population grows there will be fewer available resources to support billions more people. Ecological footprint calculators such as the one presented here can be used as a hands-on method for exploring the connections among resource consumption, environmental sustainability, and global ecosystem processes.

CHAPTER 1

CLIMATE CHANGE AND HUMAN HEALTH: A REGIONAL PREDICTIVE ASSESSMENT

Abstract

United States Historical Climatology Network (USHCN) temperature and precipitation data from twelve monitoring stations in Idaho, Montana, Wyoming were used to develop historic and predictive climate scenarios and assess the potential effects of climate change on human health in the northern Rocky Mountain region. The paper presents a method for evaluating regional climate variability that can be applied for any areas for which historical temperature and precipitation data are available. I also evaluate human health hazards that may emerge as the result of climate change. Particularly emphasized are arthropod-borne, rodent-borne, and waterborne diseases and non-infectious health hazards that are sensitive to variations in temperature and precipitation. Predicted regional climate changes include increased mean annual and seasonal temperatures; asymmetric warming characterized by steeper increases in minimum annual temperatures over maximum and mean annual temperatures; and increased annual and seasonal precipitation. Diseases that may emerge or increase in scope because of predicted climatic change include malaria, Saint Louis encephalitis, West Nile encephalitis, Rocky Mountain spotted fever, hantavirus pulmonary syndrome, plague, Cryptosporidiosis, giardiasis, heat stress, and respiratory disease.

Introduction

This paper provides a hazards assessment of climate-sensitive diseases in the northern Rocky Mountain region, and presents a method by which interactions between climate variability and human disease can be evaluated at regional scales. Specifically, I used linear trend analysis of long-term climate data provided by the United States Historical Climatology Network (USHCN) (Easterling et al. 1996) to model regional patterns in precipitation and temperature, and predict consequences of climate changes for disease emergence and human health. Linear regression of meteorological data is automated using the USHCN Trend Calculator, making this type of analysis fairly accessible to users from both technical and non-technical backgrounds. Using this methodology I address the following questions: (1) Have measurable changes in climate occurred in the northern Rocky Mountain region during the past 50 years? (2) Projecting historical trends forward, what are predicted climate conditions? (3) What are the implications of the predicted climate scenario for emergence and/or resurgence of human diseases and health hazards?

In contrast to generalized analyses that assess climate trends and health hazards on continental or global scales (Colwell and Patz 1998, Balbus and Wilson 2000, Hunter 2003, Sutherst 2004) I present a case study that targets the northern Rocky Mountain region. Health hazards assessment at regional scales may be more pertinent for development of preventive health care and environmental management policies than predictions at continental or global scales, and provide geographically accurate disease forecast maps.

The importance of climate in determining the severity, timing, and distribution of human disease has received considerable attention in recent years. The World Health Organization (WHO), Intergovernmental Panel on Climate Change (IPCC), World Watch Institute, American Academy of Microbiology, and U.S. Institute of Medicine's Committee on Emerging Microbial Threats have concluded that the effects of climate change on human health will be wide-ranging and profound (Last 1993, Jackson 1995, Colwell and Patz 1998, Kovats et al. 1998, Kovats et al. 2000, IPCC 2001a, Patz et al. 2005). These effects may occur directly as the result of increased frequency and intensity of extreme weather events, or indirectly due to reduced air and water quality, introduction of exotic species, shifting geographical and temporal distributions of disease reservoirs and/or increased abundance of disease vectors (McMichael and Haines 1997, IPCC 2001a, Patz et al. 2001, Watson and McMichael 2001, Patz et al. 2005). A brief global-scale list of health hazards likely to exhibit climate-related changes in distribution or incidence includes heat stress, malnutrition, respiratory illness, diarrheal disease, malaria, dengue fever, yellow fever, West Nile and Saint Louis encephalitides, Lyme disease, Rocky Mountain spotted fever, schistosomiasis, leptospirosis, hantavirus pulmonary syndrome, and bubonic plague. The relative threat to human health from these hazards varies significantly by geographic region, and accurate assessments must therefore account for regional landscape ecology and climatology.

Annual meteorology (weather) data from 1950-2000 from stations in Idaho, Montana, and Wyoming were used to develop linear climate change

models for the 100-year time period from 1950-2050. I use the climate forecast to assess whether any or all of the diseases listed in the paragraph above may emerge or resurge in the region in response to predicted changes in temperature and precipitation. Climate changes may be *direct* (e.g. above-average summer temperatures), or *indirect* (e.g. increased vegetation production due to above-average precipitation and a longer frost-free season). The following section provides the mechanisms by which climate influences the spread or emergence of diseases identified as potential hazards for the northern Rocky Mountain region. I next present the methods used to construct the regional climate scenario, with the aim that similar methods can be used to evaluate disease risk at alternate locations and spatial scales.

Predicted human health hazards

Climatic changes are predicted to impact human health because of increased rates and thresholds of phenological development of disease agents and hosts, shifts in geographic ranges of reservoir, host, and vector populations, reduced air quality from airborne particulate loads, and increased severity of seasonal drought conditions. Potential emergent (previously unrecognized) and resurgent (increased in scope) threats to human health in the northern Rocky Mountain region are grouped into four categories: diseases carried by insects and ticks (arthropod-borne), diseases carried by rodents (rodent-borne), diseases maintained and transmitted in water (waterborne), and non-infectious health hazards (Table 1.1). Emergence or resurgence of these diseases and

hazards may result from effects of increased temperature and precipitation on their causative agents, pathogens, reservoirs, and/or vectors.

Arthropod-borne disease

Insects and ticks (phylum Arthropoda) are sensitive to changes in climate, particularly temperature and precipitation (Cook 1992, Martens et al. 1995, Epstein et al. 1998, Adams 1999, Githeko et al. 2000). Temperature defines the geographic range of insect species within upper and lower limits and regulates incubation period, maturation rate and success, and development of disease-causing organisms within arthropod populations (Cook 1992, Martens et al. 1995, Epstein 2001, Gubler et al. 2001). Rainfall is crucial to insect reproduction and survival, particularly among those species with an aquatic larval stage (e.g. mosquitoes, mayflies, damselflies) (Cook 1992, Martens et al. 1995, Githeko et al. 2000, Gubler et al. 2001). Increased minimum temperatures promote insect overwintering and activity (Epstein et al. 1998). Arthropod-borne diseases that may emerge as threats to human health in the northern Rocky Mountain region include malaria, West Nile encephalitis, Saint Louis encephalitis, and Rocky Mountain spotted fever.

Malaria: Globally the most widespread vector-borne disease, malaria was introduced into the continental United States in the 17th century and was endemic throughout much of the country by the late 19th and early 20th centuries (Zucker 1996). By 1950, however, autochthonous malaria was eliminated from the

continental United States through vector control programs, improvements in water management and public health services, and urbanization (Adams 1999, Gubler et al. 2001). Most diagnosed cases of malaria in the United States (approximately 1,200/year) are imported (McMichael and Beaglehole 2000), but recent outbreaks of locally transmitted malaria have been reported in New Jersey, Texas, Florida, Michigan, and California during hot, wet summers (Epstein et al. 1998, Brower 2001, Gubler et al. 2001).

Malaria is transmitted to humans through the bite of *Anopheles* mosquitoes infected with parasites of the genus *Plasmodium*, including *P. falciparum*, *P. vivax*, *P. ovale*, and *P. malariae* (Zucker 1996). Climate plays a crucial role in the epidemiology of malaria through regulation of both the disease-causing agent (*Plasmodium*) and its arthropod host (anopheline mosquitoes). Development of the *Plasmodium* parasite within the mosquito is limited to external temperatures between 14-38 °C (Adams 1999), and its maturation time is significantly shorter at higher temperatures (26 days at 20 °C versus 13 days at 25 °C) (Brower 2001). The optimum temperature range to sustain adult anopheline mosquitoes is 20-25 °C (Martens et al. 1995), and within this range warmer temperatures promote disease transmission by decreasing blood digestion time and increasing feeding frequency in female mosquitoes, thus intensifying rates of disease transmission to humans (Githeko et al. 2000, Brower 2001, Small et al. 2003). Ambient temperature, humidity, and rainfall affect the lifespan of female anophelines and the abundance and quality of breeding sites (Zucker 1996) and warmer nighttime temperatures may enable survival of vector

populations at higher elevations and latitudes (Epstein et al. 1998), thus enhancing disease transmission.

Current research suggests that the greatest effects of climate change on malaria may be found at the extremes of the range of temperatures where transmission occurs and where small changes in temperature can disproportionately enhance transmission (Githeko et al. 2000, Brower 2001, Gubler et al. 2001). Diurnal and seasonal warming asymmetry at the altitude and latitude limits of malaria transmission may be critical in the spread of malaria into current areas of non-endemism (Adams 1999). Higher average, wintertime, and minimum temperatures favor the increased geographic distribution of anopheline mosquitoes (Cook 1992), enable overwintering of insect populations (Epstein et al. 1998), and sufficiently speed the cycle of mosquito reproduction and development and parasite incubation to facilitate transmission in temperate regions (Githeko et al. 2000).

Using the methodology outlined in the following section, I predict a future climate scenario for the northern Rocky Mountain region that includes higher average annual temperatures, higher minimum and nighttime temperatures, and reduced diurnal and seasonal temperature ranges which, as stated above, are implicated in the spread of malaria. Increased annual precipitation and a longer growing season are also predicted for the region, potentially affecting the creation and maintenance of critical vector breeding sites. The predicted regional shift toward a hotter, wetter climate may well be accompanied by an increase in the number of malaria vectors present, the rate of pathogen

development within host species, and incidence of disease within human populations.

Encephalitides: West Nile encephalitis and Saint Louis encephalitis are arboviral infections of the central nervous system primarily transmitted to humans by mosquitoes of the genus *Culex* (Gubler et al. 2001). Arboviral encephalitides are enzootic in animal hosts within diverse environments across the continental United States, and incidentally affect human populations (Gubler et al. 2001, Ruiz et al. 2004). Like *Anopheles* mosquitoes, *Culex* species are temperature sensitive: higher temperatures increase frequency of feeding and egg laying and rate of development, and decrease pathogen incubation period (Cook 1992, Patz et al. 2001). The overall effect is an increase in the transmission intensity of the disease to primary (avian) and incidental (mammal) hosts.

West Nile virus (WNV) was first documented in humans and animals in the United States in the summer of 1999 (Rappole et al. 2000, Peterson and Roehrig 2001), and has since been identified as the etiologic agent in approximately 16,123 cases of human encephalitis, 585 of which have resulted in death (CDC 2000, 2002b, 2002a, 2005). Birds are the amplifying hosts for WNV, which has spread across most of the continental United States at the rate of approximately 70 kilometers per month (Rappole and Hubalek 2003) presumably as the result of the migratory behavior of the host organism (Rappole et al. 2000, Peterson and Roehrig 2001). WNV is maintained in an enzootic bird-mosquito-bird cycle and is transmitted to humans mainly through bites from infected mosquitoes,

although transmission resulting from organ transplant, blood transfusion, and breast-feeding has also been documented (Gould and Fikrig 2004). In recent years West Nile virus produced the largest epidemic-scale outbreaks of arboviral encephalitis ever reported in North America (Peleman 2004), with the majority of cases of infection reported from the western United States (Roos 2004).

WNV epidemics result when flocks of amplifying hosts (avian species that exhibit high levels of viremia) promote transmission of the virus from mosquito vectors to humans and other incidental hosts (horses and most other mammals) (Rappole and Hubalek 2003, Roos 2004). Landscape factors that may be important determiners of risk areas for viral amplification include presence of wetlands and vegetation (Rappole and Hubalek 2003, Ruiz et al. 2004), which provide good habitat for both host and vector populations. These landscape features are affected by changes in temperature and precipitation, which can influence the size, distribution, and seasonal presence of wetland and vegetated areas.

Northward shifts in the geographic distribution of WNV occur in the late spring and early summer during avian migrations. Climatic conditions that favor disease cycling between arthropod and animal hosts include warm winters and summer droughts (Epstein 2001, Peterson and Roehrig 2001). Wet spring and dry summer conditions are implicated in WNV epidemics in New York City (1999) and Colorado (2003), in which periods of increased mosquito production and high rates of viral replication enhanced virus amplification and transmission, resulting in outbreaks of disease among avian reservoir species and humans and

other incidental hosts (Marra et al. 2004). Climatic conditions that facilitate such outbreaks – warm winters, summer droughts, and unusually wet spring conditions - could occur throughout the northern Rocky Mountain region in the coming half-century, prompting significant escalation of disease in human populations. The recent precipitous increase in the number of human cases and epizootic spread of WNV across the North American continent (Guptill et al. 2003, Gould and Fikrig 2004) may be in part due to climate conditions that have indirectly or directly affected pathogen, vector, and reservoir populations.

Epidemics of Saint Louis encephalitis (SLE) have occurred in Texas, Florida, Illinois, and California (Githeko et al. 2000, Gubler et al. 2001), associated with multi-day high temperature periods of 30 °C and above (Patz et al. 1996, Githeko et al. 2000, Gubler et al. 2001). Although the majority of SLE cases are clustered in the eastern United States, six of the reported 4,478 confirmed cases from 1964-1998 occurred in the northern Rocky Mountain region. Several disease prediction models have projected a northward shift of the SLE risk area in the western United States (Epstein et al. 1998, Gubler et al. 2001) as a result of climate change.

Analysis of climate data and SLE incidence shows that outbreaks are typically preceded by excessive January-February rainfall followed by July drought (Longstreth and Wiseman 1989, Githeko et al. 2000). Increased temperatures, especially at the cooler margins of the range of *Culex* species, have the potential to expand the range of the SLE vector and increase overwinter survival, enabling and increasing transmission of the disease to human

populations (Sutherst 2004). Higher annual average temperatures together with increased winter-spring precipitation, predicted for the northern Rocky Mountain region, may play a significant role in promoting shifts in disease boundaries and patterns of incidence.

Rocky Mountain Spotted Fever: Haile (1989) simulated the effects of CO_2 doubling and subsequent temperature increase on the distribution of Rocky Mountain spotted fever (RMSF) based on changes in the geographic range of its primary vector, the American dog tick (*Dermacentor variabilis*). The simulation demonstrated a clear shift from south to north in the geographic range of tick populations, including establishment within the region of interest. Because the simulation assumed no change in habitat quality or tick density, projected northward movement of vectors is solely the result of a shift in the temperature isotherm required to sustain dog tick populations (EPA 1989, Githeko et al. 2000).

RMSF is a potentially fatal disease caused by the bacterium *Rickettsia rickettsii*, transmitted to humans by *Ixodid* (hard) ticks during feeding (Thorner et al. 1998). Human cases of RMSF have been reported in every state within the United States, and initial cases were first described in 1896 and 1902 in Boise, Idaho and the Bitterroot Valley, Montana, respectively (Thorner et al. 1998). Fewer than three percent of cases reported in the U.S. from 1993-1996 were from Rocky Mountain states, and average annual incidence was 0.9 per million population (Treadwell et al. 2000). Although the major western disease vector

Dermacentor andersoni (Rocky Mountain wood tick) is present throughout the region[1], the basis for the recent decline in the incidence of RMSF observed in the western U.S. is unknown (Thorner et al. 1998).

Climate influences the timing of RMSF outbreaks through regulation of tick life cycling: warm temperatures and moist soil increase the rate of progression through the tick's four life stages (EPA 1989, Haile 1989, Githeko et al. 2000). Warm temperatures may also promote bacterial development within reservoir populations and increase vector competence (EPA 1989, Longstreth and Wiseman 1989). Future disease outbreaks in the northern Rocky Mountain region may occur as the result of increased infectivity of endemic vector populations, and northward range expansion of non-native vector populations.

Rodent-borne disease

Vector-borne diseases are sensitive to long-term changes in climate and short-term fluctuations in weather because such variations perturb the complex ecological systems that support vector populations (Meyer and Schmaljohn 2000). Increased temperature and precipitation may result in expansion of favorable habitats for reservoir populations, movement of reservoir populations to previously disease-free areas, and changes in the rate of disease transmission (Longstreth and Wiseman 1989, Jackson 1995). Climatic changes may increase the abundance and density of rodent reservoirs by increasing rates of reproduction and survival (Abbott et al. 1999, Mills et al. 1999). Human risk of disease increases with increasing likelihood of contact with disease reservoirs.

[1] http://www.cdc.gov/ncidod/dvrd/rmsf/Natural_Hx.htm

Hantavirus pulmonary syndrome: Hantavirus pulmonary syndrome (HPS) is a rodent-borne disease whose incidence has been explicitly linked to climate dynamics. The timing and severity of HPS outbreaks in human populations is attributed to fluctuations in rodent populations caused by changes in temperature and precipitation (Engelthaler et al. 1999, Mills et al. 1999). The specific mechanisms for population growth are higher rates of reproduction and survival facilitated by increased abundance of arthropod and vegetable food resources and warmer winter temperatures (Abbott et al. 1999, Mills et al. 1999, Parmenter et al. 1999).

The primary reservoir for HPS is the deer mouse (*Peromyscus maniculatus*), a common and widely distributed rodent whose range includes most of North America (Mills and Childs 1998). The main disease-causing agent of HPS, Sin Nombre virus (SNV), is endemic to deer mice within much of the species' range (Mills et al. 1997). Forty-nine cases of HPS have been diagnosed in Montana, Idaho, and Wyoming as of July 6, 2005, representing 12% of all cases reported in the United States since 1993 (n=396)[2]. HPS outbreaks in the southwestern United States are associated with episodes of above-average temperature and precipitation and local increases in rodent populations (Glass et al. 2000, Hjelle and Class 2000). Hantavirus exposure may occur as the result of recreational or domestic activities that bring humans into contact with rodents, or during dry periods when declining native food resources force rodents to forage in and around human habitations (Glass et al. 2000).

A recent long-term monitoring program in southwestern Montana identified 20% seroprevalence (SNV antibodies) in deer mice in both urban and suburban homes for 1996-1999 (Kuenzi et al. 2000), and additional data indicate prevalence of infection as high as 60% at some sites within the state (CDC 1999). Predictions for higher winter and annual temperatures and increased springtime and total annual precipitation within the Northern Rocky mountain region will likely increase resource availability and local abundance of deer mice, and increase the probability of contact between mice and humans. A contributing non-climatological factor in HPS disease risk is the continual encroachment of human populations into rodent habitats; should this trend continue in concert with climate change, the risk of disease in regional populations may be considerable.

Bubonic plague: Although an insect rather than rodent-borne disease, incidence of bubonic plague may increase because of the sensitivity of its rodent hosts to climate change. The plague bacillus *Yersinia pestis* is maintained in populations of wild rodents and is transmitted to humans by the bite of infected fleas (Parmenter et al. 1999, Gubler et al. 2001). Outbreaks of plague are associated with increased abundance of rodents and fleas and corresponding epizootics (disease epidemics in zoonotic populations) following periods of heavy winter-spring precipitation and high summer temperatures (Parmenter et al. 1999, Gubler et al. 2001, Enscore et al. 2002). High rates of reproduction in rodent populations create large pools of susceptible individuals and increase the

[2] http://www.cdc.gov/ncidod/diseases/hanta/hps/

probability of epizootics and the likelihood of disease transmission to humans (Keeling and Gilligan 2000, Enscore et al. 2002). Most human plague cases occur in New Mexico, Arizona, California, and Colorado (Gubler et al. 2001) and plague is endemic in many small mammal populations throughout the western United States (Parmenter et al. 1999).

Plague, like HPS, may experience a regional resurgence should reservoir populations increase in response to predicted climatic and environmental changes. Projected regional climate trends that may increase the density and spatial distribution of HPS and plague reservoir species are increased total annual and springtime precipitation, longer growing season, and increased minimum annual temperature. The presence of dense and well-dispersed populations of disease-carrying rodents across the landscape, the result of enhanced rates of survival and reproduction within reservoir populations conferred by warmer-than-average winters and abundance of food resources, may increase the likelihood of disease transmission to humans.

Waterborne diseases

The spread of waterborne diseases to human populations may be associated with high temperatures, increased precipitation and flooding, and agricultural runoff (Colwell and Patz 1998, Martens 1999, Epstein 2001, IPCC 2001a, Patz et al. 2001). Although more than 200 million people in the United States have access to treated drinking water, millions of cases of waterborne disease are reported per year (Patz et al. 2001). Cryptosporidiosis, the most prevalent waterborne disease in the United States (IPCC 1997), results from

infection with the protozoan *Cryptosporidium parvum*. *C. parvum* are chlorine-resistant, thick-walled oocysts that can exist outside the body for long periods of time (Guerrant 1997), and are passed between humans and many mammal species through contact with food, soil, water, or surfaces that have been contaminated with feces from infected individuals (Patz et al. 2000b, Curriero et al. 2001). Major outbreaks of Cryptosporidiosis have occurred in the United Kingdom and in Milwaukee, Wisconsin, and it has been estimated that 13% of treated municipal water in the United States is contaminated with *Cryptosporidium* oocysts (Patz et al. 2000b). Agricultural areas are a primary source for the oocytes, which may be washed into municipal water supplies by heavy surface runoff associated with increased winter precipitation and intensive early-season heating (Curriero et al. 2001, Hunter 2003). Giardiasis, a similar diarrheal disease caused by infection with *Giardia* protozoans, may also increase in incidence with heavy precipitation and flooding events (Martens 1999, Patz et al. 2001). Both Cryptosporidiosis and giardiasis are likely to increase in frequency and magnitude under the predicted climate scenario for the northern Rocky Mountain region, which includes increased mean annual precipitation and higher spring temperatures.

Non-infectious health hazards

Non-infectious emergent human health hazards considered for the region are heat stress and respiratory disease. Predicted changes in temperature and

precipitation may affect the frequency and severity of reported cases, resulting in increased morbidity and mortality.

Heat stress may be one of the more direct and immediate human health consequences of predicted climate change. Heat-related illness, including heat cramps, heat stroke, heat exhaustion, and heat death, can result from long-term exposure to high ambient temperatures or from increased frequency of heat waves (EPA 1997, Martens 1999, Patz et al. 2005). Overall death rates have been observed to increase substantially with temperature extremes above baseline in a number of cities in the northern United States and Canada (Patz et al. 2000a). Heat waves have the greatest impact on human health when they occur in early summer before populations have acclimated, for long durations, and under conditions of higher nighttime minimum temperatures (Balbus and Wilson 2000, Patz et al. 2000a, Patz et al. 2005). Heat island effects, caused by the nighttime release of stored energy in urban environments, exacerbate the severity of temperature extremes (Martens 1999, Balbus and Wilson 2000). Risk of heat-related illness is highest in young children, the elderly, the sick, and those who lack access to air-conditioning (Patz et al. 2000a, Patz et al. 2001).

Respiratory diseases including asthma, hay fever, and allergies are associated with the presence of irritants such as mold, pollen, ozone, natural hydrocarbons, and anthropogenic emissions (EPA 1989, 1998b, 1998a, Patz et al. 2001). Incidence of respiratory illness is projected to increase in hotter, wetter climates that favor growth of molds, increased pollen production, increase in ground-level ozone concentration, terpene production by trees and shrubs, and

power plant emissions from increased air conditioning use (EPA 1998b, 1998a, Patz et al. 2001). In addition, seasonal drought conditions prompted by rising temperatures may increase the frequency and severity of wildland fires, releasing significant loads of respiratory pollutants (Epstein 2001). Extreme temperatures increase asthmatic sensitivity (Martens 1999), amplifying initial health effects. Predicted regional increases in precipitation and length of the frost-free period will favor the growth and proliferation of molds and pollen-producing plants; high temperatures may increase the concentrations of ground level ozone and terpenes; and, as historically demonstrated, drought-like summer conditions may increase the incidence of respiratory illness associated with wildfires.

Large-scale climate trends

A global average surface temperature increase of approximately 0.6 °C has been observed over the 20th century (IPCC 2001a, Easterling 2002), and global temperatures are predicted to increase by 1.4-5.8 °C over the next 100 years (IPCC 2001b, Patz et al. 2005). Such changes are neither uniform nor symmetric: increases in surface temperature are greater at higher latitudes and on land surfaces, and daily minimum temperatures are increasing at about twice the rate of daily maximum temperatures (Karl et al. 1993, Easterling et al. 2000, Watson and McMichael 2001, Easterling 2002, Walther et al. 2002). Winter warming is occurring much faster than overall warming, especially at higher latitudes (Karl et al. 1993, Epstein 2001). Temperature data for the United States for the period from 1949-1999 demonstrate trends toward fewer number of frost

days (days when the minimum temperature is below 0 °C), an earlier date of last spring freeze, a later date of first fall frost, and a longer frost-free season (difference between the last-spring freeze and the first-fall frost) (Easterling 2002). Annual precipitation over climate zones during the past century shows an increase from 7% to 12% within the latitude range of 30 °N to 85 °N, with an increasing fraction of precipitation deposited as rain rather than snow (IPCC 2001b). In addition, there has been an increase in the frequency and intensity of precipitation events in the United States during the 20th century (Karl and Knight 1998).

Asymmetry and non-uniformity of changes in temperature and precipitation underscores the importance of using appropriately scaled climate data to forecast disease trends. In the following section meteorological data from the USHCN are used to model and predict climatic conditions to provide a more spatially explicit scenario of potential emergent and resurgent climate-sensitive human health hazards. I examine trends to determine whether the northern Rocky Mountain region is experiencing climate changes congruent with those observed at the continental scale. In particular I evaluate whether daily minimum temperature is increasing disproportionately to daily maximum temperature, if winter warming is occurring faster than overall warming, and whether overall precipitation is increasing.

Methods

This methodology offers a framework in which long-term meteorological data sets can be used to provide spatially explicit disease risk assessments. The methods described here were used to forecast changes in a number of temperature and precipitation variables; using these results I identify regional health hazards with sufficient climatic sensitivity to suggest that predicted climate trends may increase the scope or incidence of these threats in human populations.

Data from meteorological stations located within Idaho, Montana, and Wyoming were used to develop an historical climate scenario for the past half-century (A.D. 1950 through 2000) and predict general regional climate conditions present for the year A.D. 2050. Meteorological stations were selected from a network of 1,221 available stations within the conterminous United States, whose monthly temperature and precipitation data are compiled by the Carbon Dioxide Information Analysis Center (CDIAC) and the National Climatic Data Center (NCDC). Station selection was based on a defined geographic location within the northern Rocky Mountain region (west of the Continental Divide, within Idaho, Montana, or Wyoming), relatively mountainous elevation (greater than or equal to 3,000 feet [914 meters] above sea level), and data availability (data reported through the year 2000 with no more than a total of 10 years' missing data for the period of 1950 through 2000). Twelve meteorological stations met these criteria and were used in the analysis (Table 1.2, Figure 1.1).

The U.S. Historical Climatology Network (USHCN) Trend Calculator (Easterling et al. 1996) provides linear regression statistics and graphical plots for each climate variable included in the analysis: mean annual temperature; minimum and maximum annual temperature; mean winter, spring, summer, and fall temperature; and total annual and winter, spring, summer, and fall precipitation. Although the entire set of variables available in the USHCN data base includes mean, maximum, and minimum temperature and total precipitation at annual, seasonal, and monthly time steps, I included only those variables that are widely implicated in the disease ecology literature as important factors in disease emergence or resurgence.

The Trend Calculator allows users to select meteorological stations by state and station name, and provides a longitude, latitude, and elevation for each station. Users may interactively select climate variables of interest, and the temporal range over which the variable will be modeled. I included observed meteorology data for the years 1950 through 2000 from four Idaho stations (Ashton, Challis, Lifton, Salmon), four Montana stations (Anaconda, Fortine, Hamilton, Philipsburg), and four Wyoming stations (Alta, Evanston, Moran, Rock Springs). The regression statistics generated by the Trend Calculator allow for linear extrapolation beyond the temporal range of the data, useful for predicting future climatic conditions. I substituted the model years (1950, 2000, and 2050) into those equations, generated through regression of annual climate observations against year, to model historical climate conditions and construct a predictive climate scenario.

Results and discussion

Temperature

Tables 1.3a and 1.3b show modeled temperature data for each station, for the years 1950, 2000, and 2050. With the exception of a single station (Anaconda, MT) mean annual temperature increased for all stations over the 100 year period of the analysis. Minimum annual and mean spring and summer temperatures increased for all stations, and maximum annual, mean winter, and mean fall temperatures increased across most stations in the analysis. These data suggest that regional climate trends conform to large-scale warming predictions, including higher average, minimum, and winter temperatures. It is important to note that model predictions assume that climate changes follow a linear trend over time, an assumption that may produce a conservative estimate of long-term climate change. For example, although the global average temperature has increased by about 0.6 °C in the last 100 years, a 1.4 to 5.8 °C increase is predicted for the end of the 21st century (IPCC 2001b, Patz et al. 2005), suggesting that warming patterns may accelerate faster than simple linear model predictions.

For each variable in the analysis data for selected model years were averaged across stations to produce a regional-scale assessment; these predicted regional temperature trends are listed as mean values in Tables 1.3a and 1.3b. In addition predicted temperature change per 50 year period was calculated for both individual stations and for the region, to provide a discrete and

incremental measure of climate change for the 2050 target year. Absolute change per 50 year period is calculated for each temperature variable in the analysis as the difference between start and end period values; for example:

$$\Delta MAT_{50} = MAT_{Time2} - MAT_{Time1}$$

is the predicted change per 50 year period for mean annual temperature (MAT), Time2 is a 50 year endpoint (e.g. 2050) and Time1 is a 50 year start point (e.g. 2000) (Table 1.4). Regional mean values are the average of predicted incremental changes for all stations. The general regional trend was for an increase in mean, minimum, and maximum annual temperature and mean seasonal temperature per 50 year period, although opposite trends (decrease in temperature) were predicted for some individual stations.

At a regional scale the model results suggest seasonal warming asymmetry, with a larger predicted increase in mean spring and winter temperatures over mean annual temperatures. In addition regional predictions are non-uniform, such that the predicted increase in minimum temperature is 65% larger than the predicted increase in maximum temperature (Figure 1.2). Non-uniformity in warming patterns at the lower limits of temperature extremes months may increase the length of the growing season and frost-free period, and contribute to the emergence and increased distribution of disease vectors and reservoirs that thrive in warmer, more productive environments.

Although regional predictions are consistent with global observations and predictions for large increases in winter and minimum temperatures over annual mean and maximum temperatures (Easterling 2002), it is important to note that

there is some error inherent in scaling point based data to a regional scale. For example, upper outliers in minimum annual temperature and mean winter temperature in Figure 1.2, observed for Rock Springs, WY, strongly influence the regional scenario constructed for those variables. Comparison of actual versus predicted values for minimum annual temperature for 1950-2000 at the Rock Springs weather station suggests that missing observations may influence the predicted warming trend through sample size limitations (Figure 1.3a); however, the mean winter temperature record for Rock Springs includes only two missing data points (1978 and 2000) but still demonstrates a strong warming trend (Figure 1.3b), suggesting that estimates for increased minimum and winter temperatures are based on valid climate trends. Assessment of outliers is an important component of this and other climate predictions, to determine whether predicted patterns result from observation errors or as the result of actual variability.

Precipitation

Station-specific and regional average precipitation estimations for the years 1950, 2000, and 2050 are shown in Table 1.5. As with temperature, precipitation estimations are scaled to the region through averaging, shown as mean values. General trends are for a regional increase in total annual and seasonal precipitation; however, variability is present across stations both in the direction and magnitude of precipitation trends from 1950-2050. Increase in summer precipitation was predicted for all stations, and increase in fall and total

annual precipitation was predicted for a majority of stations; and winter precipitation was predicted to decrease at six of the 12 stations in the analysis (Idaho: Ashton, Salmon; Montana: Anaconda, Fortine, Philipsburg; Wyoming: Evanston). No obvious patterns exist in terms of geographic distribution of these six stations, although with the exception of Evanston, WY, all are located below 6,000 feet in elevation (Table 1.2). Predicted winter drying trends for these stations may reflect interactions between topography, surface temperature, and atmospheric circulation patterns.

Predicted change in precipitation per 50 year period is calculated for each variable in the analysis as the difference between start and end period values; for example total annual precipitation (TAP) is calculated as:

$$\Delta TAP_{50} = TAP_{Time2} - TAP_{Time1}$$

where Time2 is a 50 year endpoint (e.g. 2050) and Time1 is a 50 year start point (e.g. 2000).

The regional change in total annual precipitation per 50 year period for the northern Rocky Mountains is predicted to be 2.81 inches per 50 years (Table 1.6). An asymmetric increase in spring precipitation over winter, summer, and fall precipitation is also evident, possibly caused by increased spring temperatures that favor rainfall over snowfall, or atmospheric circulation patterns that bring increased springtime moisture to the region. The seasonal distribution of precipitation (modeled, 1950-2050) is as follows: spring precipitation accounts for the highest fraction of accumulated moisture, followed by fall, summer, and winter summer precipitation (Table 1.6, Figure 1.4). These results align with

large-scale climate predictions for increased precipitation over the North American continent (IPCC 2001b).

As with temperature there are outliers in precipitation data that influence the predicted regional climate scenario. In particular, total annual and spring precipitation at Alta, WY and Fortine, MT, fall noticeably outside the mean values for all stations; the Alta station is characterized by higher than average values, while at the Fortine station total annual and springtime precipitation were lower than average (Figure 1.4). Because the magnitude and direction of these trends are outstanding among the full 12 station data set, a comparison of actual versus predicted total annual and spring precipitation data for 1950-2000 was made (Figures 1.5a and 1.5b, Figures 1.6a and 1.6b). Data plots for the Alta and Fortine stations suggest that predictions for drastically increased total annual precipitation (Alta) and decreased total annual precipitation (Fortine) reflect actual patterns in observed meteorology (Figures 1.5a and 1.5b). Similarly, predictions for significant changes in spring precipitation at Alta (increase) and Fortine (decrease) appear to be based on valid trends in annual meteorology. Thus, incorporating these outliers into the regional climate prediction model is justified as these data reflect climate variability within the region.

Conclusions

Seasonal and annual climatic fluctuations can affect human health through complex interactions among disease agents, reservoirs, and vectors and the environment. Regional climatic changes predicted for the northern Rocky

Mountains include increased average annual and minimum temperatures and increased total annual and seasonal precipitation. Predicted changes are asymmetrical and non-uniform, including steeper increases in minimum over maximum annual temperatures and disproportionate increases in spring precipitation. Other climatic changes likely to occur include reduced diurnal and seasonal temperature ranges; higher minimum day- and nighttime temperatures; earlier dates of last spring frost; fewer frost days and longer frost-free periods. The consequences of these changes for human health may be emergence or resurgence of arthropod-, rodent-, and waterborne diseases and non-infectious health hazards, including: malaria, Saint Louis encephalitis, West Nile encephalitis, Rocky Mountain spotted fever, hantavirus pulmonary syndrome, plague, cryptosporidiosis, giardiasis, heat stress, and respiratory disease. Changes in scope or incidence of these diseases are closely coupled with fluctuations in long-term climate and short-term weather, because abiotic factors play a critical role in determining vector habitat suitability, pathogen transmission rates and pathogenesis, presence and longevity of host organisms, and human susceptibility to disease.

The methods presented here for predicting climate change and identifying potential related health hazards are descriptive. The study provides a simple and accessible framework for forecasting climate trends based on meteorological data that are available for stations throughout the continental United States, together with a regional scenario of emergent health hazards in the context of predicted climatic change. Similar scenarios may be developed for any region of

interest, incorporating any subset of available meteorological data. These data can then be compared to temperature and precipitation thresholds that determine the distribution of pathogens and vectors, to determine whether, when, and where diseases may emerge. Although this type of analysis cannot provide definitive answers, the method can be used as triage, to focus attention on those hazards that pose the greatest threats to human health.

Drawbacks of this modeling method include failure to account for complex, non-linear feedback effects and climate dynamics, assumptions of linearity, and the relatively small number of meteorological stations used in the analysis; however, my predictions closely match published predictions for regional- and continental-scale climate change. Recent research indicates that changes in precipitation and temperature can interactively affect ecosystems, significantly, producing amplified responses above those expected with independent effects (Shaver et al. 2000, Alto and Juliano 2001, Harvell et al. 2002). Although I do not address such nonlinear effects here, their treatment in more complex assessments is recommended.

The simple nature of this analysis and the generality of its findings underscore the need for development of complex, scaled models that incorporate the linear and non-linear dynamics among pathogens, their host and reservoir species, and the environment. The linkages between climate and disease are complex, and operate within the context of ecological interactions among pathogens, hosts, and vectors, landscape configuration and composition, and public health strategies. No simple model (and often not complex ones) can

accurately predict when, where, and how diseases will respond to climate variability, although such models are badly needed. Complex models, where they do exist, are mainly region-specific and by definition cannot be successfully applied to other areas (Enscore et al. 2002, Glass et al. 2002, Bi et al. 2003, Brownstein et al. 2003, Zhou et al. 2004). Clearly the need still exists for models or methods useful for assessing effects of climate change on disease hazards at diverse scales and geographic locations.

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Table 1.1 Emergent and resurgent diseases and health hazards predicted for the northern Rocky Mountain region. Predictions based on changes in temperature and precipitation projected by the regional climate analysis.

Climate Parameter	Predicted increase per 50 years	Disease emergence/resurgence
Mean annual temperature	1.38 °C	malaria, West Nile encephalitis, Saint Louis encephalitis, Rocky Mountain spotted fever, hantavirus pulmonary syndrome
Minimum annual temperature	2.05 °C	malaria, Saint Louis encephalitis, Rocky Mountain spotted fever, hantavirus pulmonary syndrome, plague
Maximum annual temperature	0.71 °C	heat stress, respiratory disease
Mean winter temperature	1.23 °C	malaria, Saint Louis encephalitis, Rocky Mountain spotted fever, hantavirus pulmonary syndrome, plague
Mean spring temperature	2.62 °C	Cryptosporidiosis, giardiasis
Mean summer temperature	1.11 °C	malaria, West Nile encephalitis, Saint Louis encephalitis, plague, heat stress, respiratory disease
Mean fall temperature	0.55 °C	heat stress, respiratory disease
Total annual precipitation	2.81 cm	
Winter precipitation	0.40 cm	malaria, West Nile encephalitis, Saint Louis encephalitis, Rocky Mountain spotted fever, hantavirus pulmonary syndrome, plague, Cryptosporidiosis, giardiasis, respiratory disease
Spring precipitation	1.13 cm	
Summer precipitation	0.53 cm	
Fall precipitation	0.74 cm	

Table 1.2 Site characteristics of meteorological stations used in the climate prediction scenario

Station Name	State	Latitude	Longitude	Elevation (feet)	Station Code
ASHTON	ID	44.07	-111.45	5260	100470
CHALLIS	ID	44.50	-114.23	5175	101663
LIFTON	ID	42.12	-111.30	5926	105275
SALMON	ID	45.18	-113.90	3931	108080
ANACONDA	MT	46.13	-112.95	5280	240199
FORTINE	MT	48.78	-114.90	3000	243139
HAMILTON	MT	46.25	-114.15	3529	243885
PHILIPSBURG	MT	46.32	-113.30	5270	246472
ALTA	WY	43.78	-111.03	6430	480140
EVANSTON	WY	41.27	-110.95	6825	483100
MORAN	WY	43.85	-110.58	6798	486440
ROCK SPRINGS	WY	41.60	-109.07	6741	487845

Table 1.3a Modeled annual temperature (°C) for 12 meteorological stations in Idaho, Montana, and Wyoming based on USHCN climate data.

	Mean Annual			Minimum Annual			Maximum Annual		
Station	1950	2000	2050	1950	2000	2050	1950	2000	2050
ASHTON, ID	4.13	5.62	7.12	-3.66	-1.13	1.40	11.94	12.21	12.49
CHALLIS, ID	5.86	7.59	9.32	-1.65	0.38	2.41	13.34	14.78	16.22
LIFTON, ID	4.46	5.60	6.73	-2.55	-1.66	-0.77	11.44	12.83	14.22
SALMON, ID	6.73	7.18	7.64	-1.84	0.04	1.92	15.26	14.29	13.32
ANACONDA, MT	6.01	5.47	4.93	1.04	-2.20	-5.44	10.89	13.13	15.38
FORTINE, MT	4.82	6.62	8.41	-2.57	-0.25	2.08	12.19	13.46	14.72
HAMILTON, MT	6.62	7.74	8.85	-0.13	0.54	1.21	13.35	14.91	16.47
PHILIPSBURG, MT	4.00	4.85	5.70	-3.72	-2.41	-1.10	11.68	12.08	12.47
ALTA, WY	4.01	4.17	4.32	-3.60	-2.24	-0.88	11.64	10.67	9.70
EVANSTON, WY	3.21	5.21	7.22	-6.04	-1.94	2.23	12.45	12.34	12.23
MORAN, WY	0.96	2.40	3.83	-7.09	-5.42	-3.76	8.99	10.19	11.40
ROCK SPRINGS, WY	1.33	6.27	11.22	-9.06	-0.01	9.03	11.68	12.53	13.38
Mean Value	**4.35**	**5.73**	**7.11**	**-3.41**	**-1.36**	**0.69**	**12.07**	**12.79**	**13.50**

Table 1.3b Modeled seasonal temperature (°C) for 12 meteorological stations in Idaho, Montana, and Wyoming based on USHCN climate data.

	Mean Winter			Mean Spring			Mean Summer			Mean Fall		
Station	**1950**	**2000**	**2050**	**1950**	**2000**	**2050**	**1950**	**2000**	**2050**	**1950**	**2000**	**2050**
ASHTON, ID	-7.24	-5.71	-4.19	3.10	5.10	7.09	15.48	16.84	18.20	5.30	5.87	6.44
CHALLIS, ID	-5.68	-4.28	-2.89	5.05	8.20	11.36	17.57	18.84	20.10	6.75	7.42	8.10
LIFTON, ID	-7.38	-6.30	-5.22	2.60	5.28	7.97	16.86	17.26	17.66	5.70	6.00	6.29
SALMON, ID	-4.78	-5.26	-5.74	6.39	8.24	10.10	18.15	18.86	19.56	7.12	6.96	6.80
ANACONDA, MT	-3.42	-4.43	-5.44	3.46	5.38	7.30	16.76	15.72	14.69	6.96	5.13	3.29
FORTINE, MT	-5.30	-4.41	-3.53	4.45	7.30	10.15	15.23	17.27	19.31	5.04	5.90	6.77
HAMILTON, MT	-3.02	-2.25	-1.47	5.87	8.04	10.22	17.03	17.95	18.86	6.61	7.24	7.88
PHILIPSBURG, MT	-5.13	-4.58	-4.03	2.15	4.91	7.67	14.06	14.51	14.96	4.69	4.82	4.96
ALTA, WY	-6.37	-6.47	-6.58	2.06	3.29	4.51	15.18	15.56	15.94	5.25	4.60	3.95
EVANSTON, WY	-7.69	-5.36	-3.04	1.34	4.60	7.86	14.80	16.06	17.33	4.25	5.74	7.30
MORAN, WY	-10.19	-9.62	-9.06	-0.77	1.88	4.53	12.42	14.24	16.05	2.44	3.02	3.61
ROCK SPRINGS, WY	-12.92	-5.70	1.52	0.79	5.68	10.56	14.46	18.23	21.99	2.35	6.24	10.14
Mean Value	**-6.59**	**-5.36**	**-4.14**	**3.04**	**5.66**	**8.28**	**15.67**	**16.78**	**17.89**	**5.20**	**5.75**	**6.29**

Table 1.4 Modeled temperature change (°C) per 50 years for 12 meteorological stations in Idaho, Montana, and Wyoming based on USHCN climate data.

Station	Mean Annual	Minimum Annual	Maximum Annual	Mean Winter	Mean Spring	Mean Summer	Mean Fall
ASHTON, ID	1.50	2.53	0.28	1.52	2.00	1.36	0.57
CHALLIS, ID	1.73	2.03	1.44	1.40	3.15	1.26	0.67
LIFTON, ID	1.13	0.89	1.39	1.08	2.69	0.40	0.30
SALMON, ID	0.46	1.88	-0.97	-0.48	1.85	0.71	-0.16
ANACONDA, MT	-0.54	-3.24	2.24	-1.01	1.92	-1.03	-1.84
FORTINE, MT	1.79	2.32	1.26	0.88	2.85	2.04	0.87
HAMILTON, MT	1.11	0.67	1.56	0.78	2.18	0.92	0.64
PHILIPSBURG, MT	0.85	1.31	0.39	0.55	2.76	0.45	0.14
ALTA, WY	0.15	1.36	-0.97	-0.11	1.22	0.38	-0.65
EVANSTON, WY	2.01	4.18	-0.11	2.33	3.26	1.27	1.56
MORAN, WY	1.44	1.66	1.20	0.57	2.65	1.81	0.58
ROCK SPRINGS, WY	4.94	9.04	0.85	7.22	4.89	3.77	3.90
Mean Value	**1.38**	**2.05**	**0.71**	**1.23**	**2.62**	**1.11**	**0.55**

Table 1.5 Modeled precipitation (inches) for 12 meteorological stations in Idaho, Montana, and Wyoming based on USHCN climate data.

	Total Annual			Winter			Spring			Summer			Fall		
Station	**1950**	**2000**	**2050**	**1950**	**2000**	**2050**	**1950**	**2000**	**2050**	**1950**	**2000**	**2050**	**1950**	**2000**	**2050**
ASHTON, ID	18.37	20.63	22.89	6.10	6.00	5.90	4.46	5.86	7.26	3.72	4.04	4.36	4.09	4.73	5.37
CHALLIS, ID	4.68	13.45	22.21	0.01	4.69	9.38	1.48	3.35	5.21	2.26	2.59	2.92	0.93	2.81	4.69
LIFTON, ID	9.16	12.33	15.50	1.99	2.38	2.77	2.54	3.79	5.04	2.42	2.82	3.21	2.21	3.34	4.47
SALMON, ID	9.32	10.30	11.28	1.99	1.83	1.66	2.49	2.77	3.05	3.11	3.26	3.41	1.72	2.44	3.16
ANACONDA, MT	13.94	13.64	13.34	2.90	1.51	0.13	3.63	4.11	4.59	4.55	5.22	5.89	2.87	2.80	2.73
FORTINE, MT	19.04	14.02	9.05	5.00	2.10	0.00	4.72	3.39	2.06	5.02	5.45	5.89	4.31	3.07	1.90
HAMILTON, MT	12.83	13.72	14.61	3.07	3.13	3.20	3.09	3.75	4.42	3.41	3.93	4.46	3.26	2.90	2.53
PHILIPSBURG, MT	13.92	15.24	16.56	2.20	1.50	0.80	3.86	5.04	6.21	5.05	5.29	5.53	2.82	3.42	4.02
ALTA, WY	18.09	27.64	37.20	4.07	7.20	10.33	4.90	8.44	11.98	4.73	5.89	7.04	4.40	6.12	7.84
EVANSTON, WY	9.86	12.10	14.35	2.20	1.91	1.62	3.01	3.64	4.28	2.21	3.24	4.26	2.44	3.32	4.19
MORAN, WY	21.44	26.89	32.34	7.86	9.01	10.16	5.26	7.07	8.89	3.54	4.48	5.42	4.77	6.32	7.87
ROCK SPRINGS, WY	5.86	10.20	14.54	0.79	1.76	2.74	1.64	3.44	5.25	2.12	2.34	2.56	1.32	2.65	3.99
Mean Value	**13.04**	**15.85**	**18.65**	**3.18**	**3.59**	**4.06**	**3.42**	**4.56**	**5.69**	**3.51**	**4.05**	**4.58**	**2.93**	**3.66**	**4.40**

Table 1.6 Modeled precipitation change (inches) per 50 years for 12 meteorological stations in Idaho, Montana, and Wyoming based on USHCN climate data.

Station	Total Annual	Winter	Spring	Summer	Fall
ASHTON, ID	2.26	-0.10	1.40	0.32	0.64
CHALLIS, ID	8.76	4.69	1.87	0.33	1.88
LIFTON, ID	3.17	0.39	1.25	0.39	1.14
SALMON, ID	0.98	-0.17	0.28	0.15	0.72
ANACONDA, MT	-0.30	-1.39	0.48	0.67	-0.07
FORTINE, MT	-4.96	-2.10	-1.33	0.43	-1.17
HAMILTON, MT	0.89	0.07	0.66	0.53	-0.36
PHILIPSBURG, MT	1.32	-0.70	1.18	0.24	0.60
ALTA, WY	9.55	3.13	3.54	1.16	1.72
EVANSTON, WY	2.25	-0.29	0.64	1.03	0.87
MORAN, WY	5.45	1.15	1.82	0.94	1.55
ROCK SPRINGS, WY	4.34	0.97	1.81	0.22	1.34
Mean Value	**2.81**	**0.47**	**1.13**	**0.53**	**0.74**

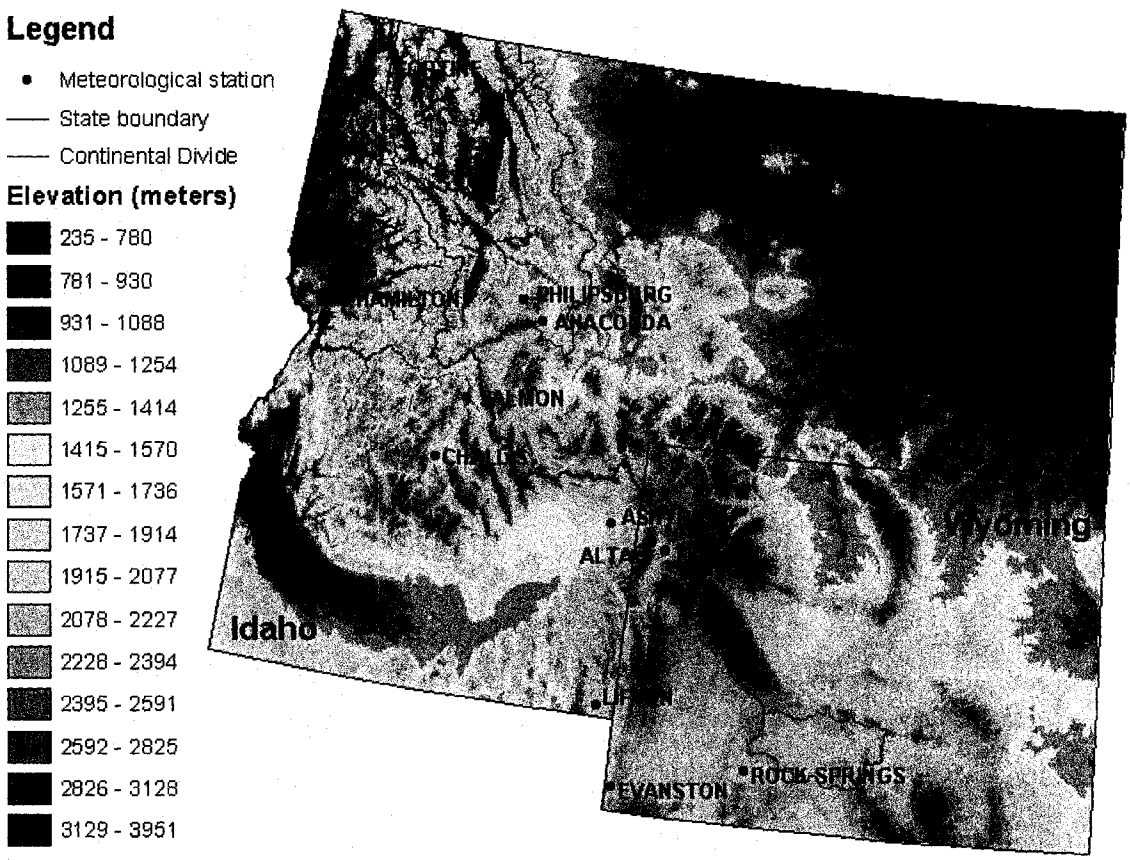


Figure 1.1 Location of meteorological stations used in the climate prediction scenario. Stations are within the northern Rocky Mountain region (Idaho, Montana, and Wyoming). Background is a 250 meter digital elevation model (DEM).

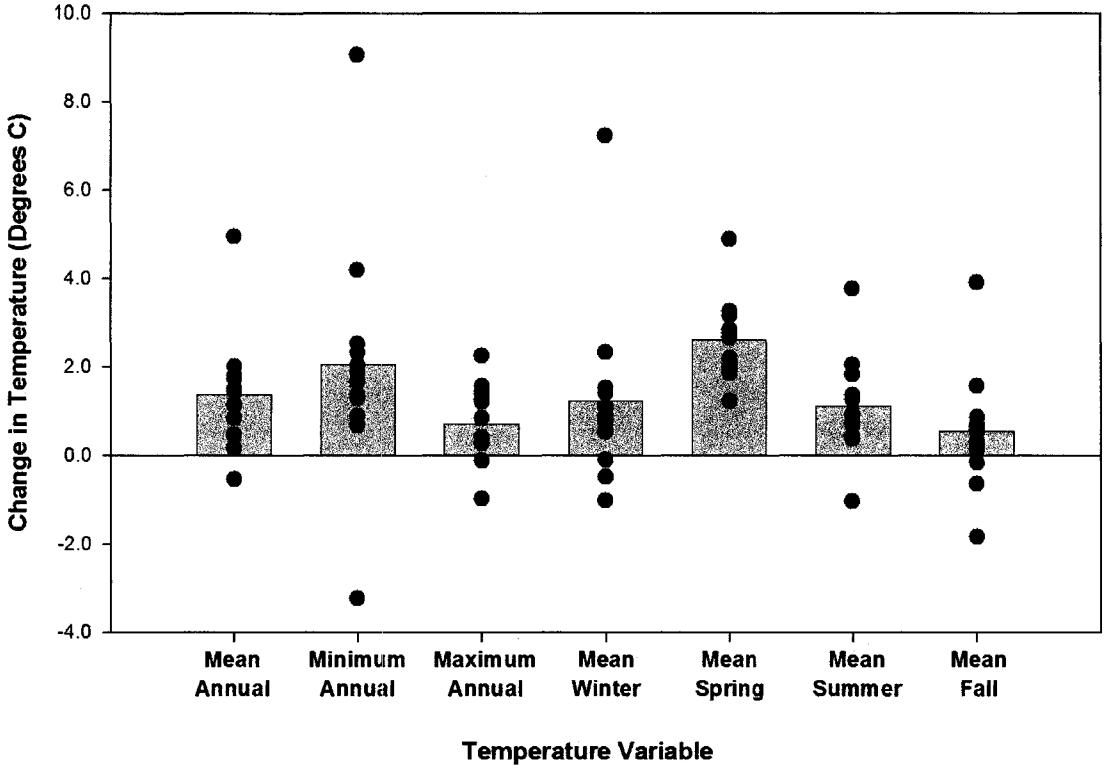
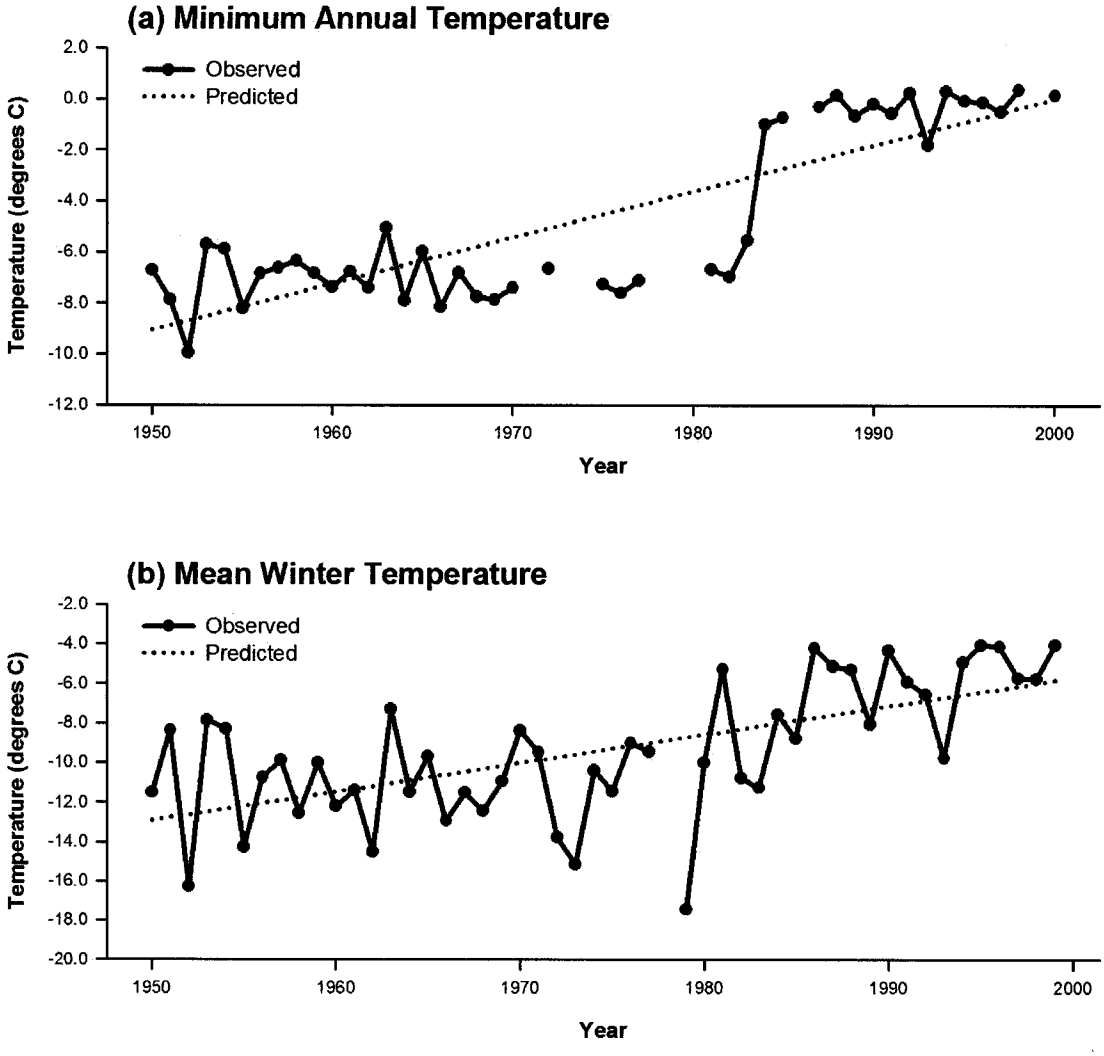


Figure 1.2 Average temperature change (°C) per 50 year period. Shaded bars are mean values and closed black circles are individual data points that contribute to the mean value. Note asymmetry in predicted increases in minimum, spring, and winter temperatures over maximum and mean annual temperatures.



Figures 1.3a and 1.3b Observed (solid line) and predicted (dotted line) minimum annual temperature (a) and mean winter temperature (b) for Rock Springs, WY (1950-2000). Missing data values are shown as breaks in the solid line plots.

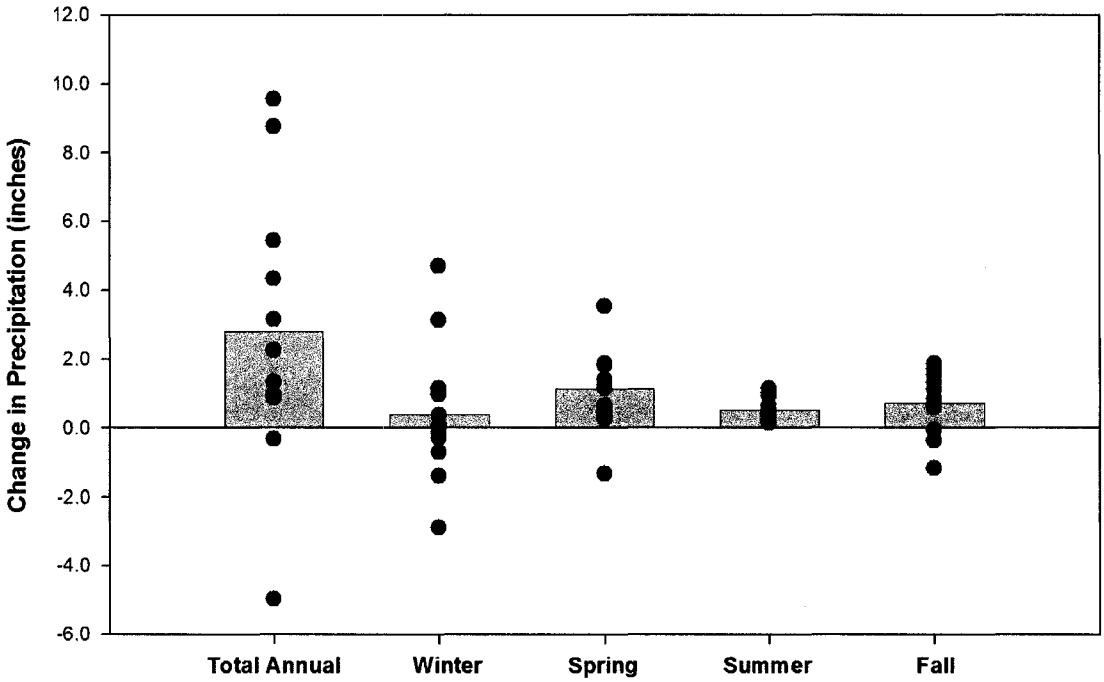
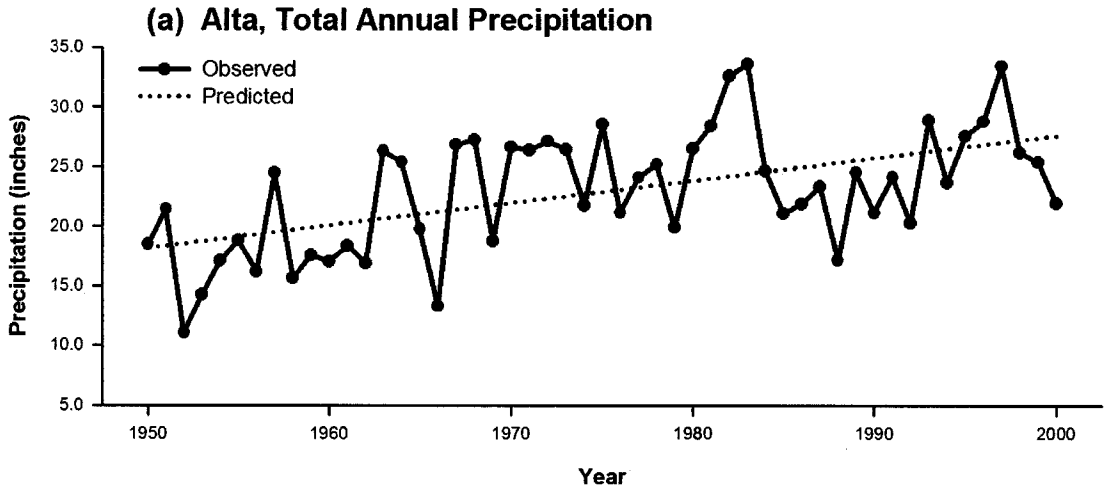
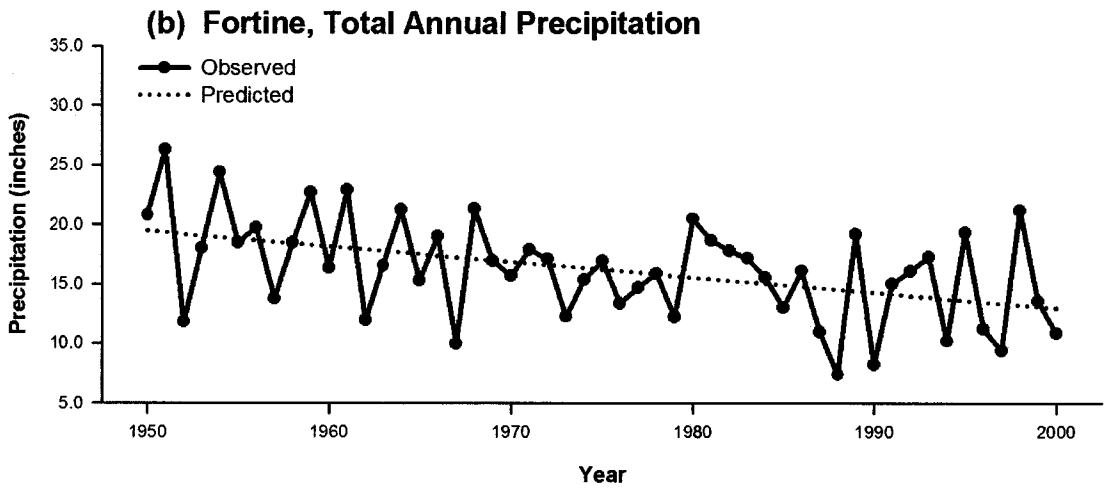
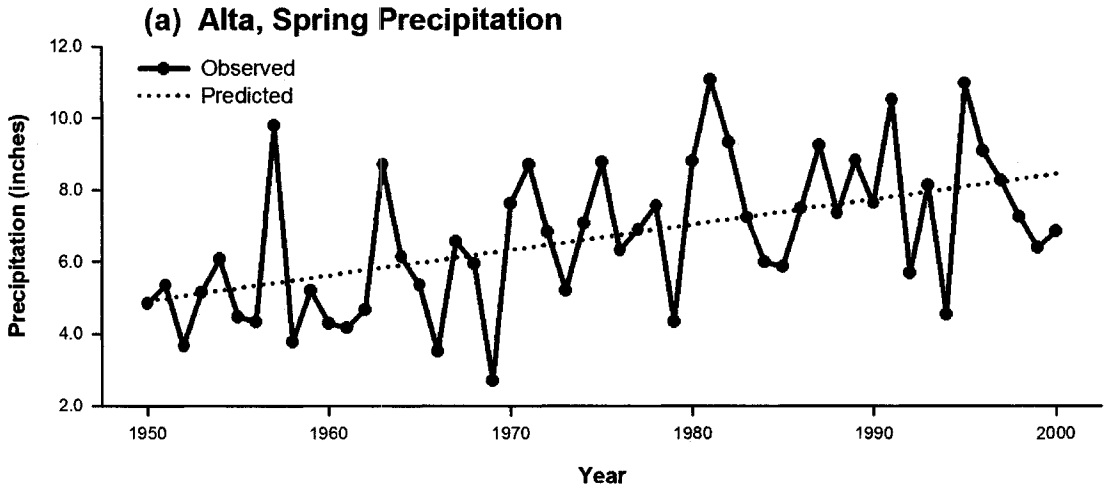


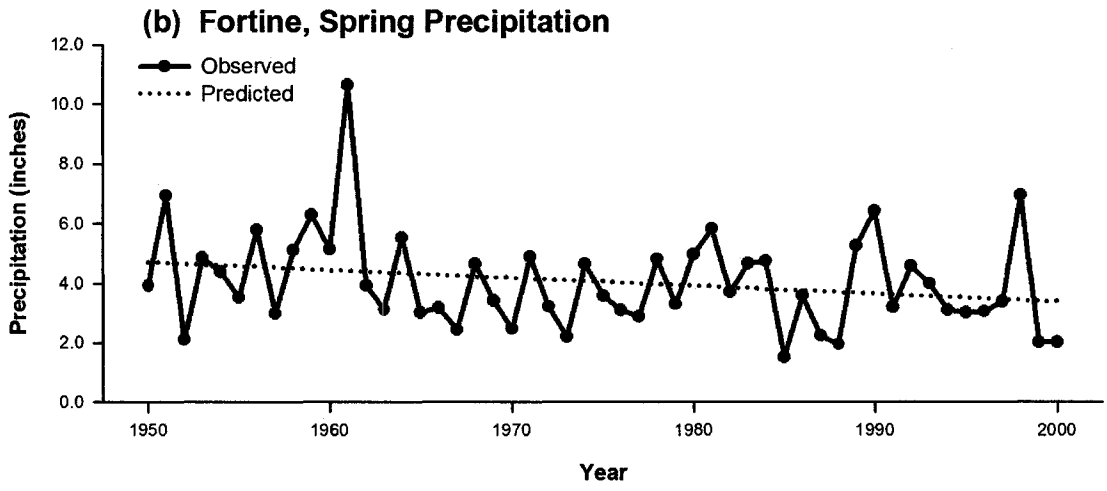
Figure 1.4 Average precipitation change (inches) per 50 year period. Shaded bars are mean values and closed black circles are individual data points that contribute to the mean value. Note asymmetry in predicted increases in spring versus winter and summer precipitation.





Figures 1.5a and 1.5b Observed (solid line) and predicted (dotted line) total annual precipitation at Alta, WY (a) and Fortine, MT (b) (1950-2000).





Figures 1.6a and 1.6b Observed (solid line) and predicted (dotted line) spring precipitation at Alta, WY (a) and Fortine, MT (b) (1950-2000).

CHAPTER 2

FORECASTING HANTAVIRUS PULMONARY SYNDROME OUTBREAKS USING REMOTELY SENSED DATA: LINKING BIOCLIMATOLOGY AND MODIS GROSS PRIMARY PRODUCTIVITY WITH VECTOR POPULATION DYNAMICS

Abstract

Relationships among rainfall, resource abundance, and *Peromyscus maniculatus* rodents were modeled using precipitation data from the National Climatic Data Center, vegetation gross primary productivity (GPP) from the Moderate Resolution Imaging Spectroradiometer (MODIS) and rodent population data from three longitudinal study sites in Montana. *P. maniculatus* (deer mice) are the main reservoir host for Sin Nombre virus (SNV), the primary disease agent of hantavirus pulmonary syndrome (HPS). *P. maniculatus* populations fluctuate widely, and increasing population density may significantly affect human risk of disease through increased probability of contact between humans and infected animals. Changes in weather and plant productivity have been noted as likely catalysts of population irruptions, and monitoring and modeling of these phenomena may allow for development of early-warning systems for disease risk. Results from this study showed that at an annual time scale MODIS GPP and rodent density were strongly correlated for 2000 through 2003. Data from 2004 fell as outliers in the distribution, weakening correlations across all study sites. Although annual-scale vegetation abundance and rodent population density were associated, other ecological processes likely play a dominant role in influencing rodent population variability. Such processes may include threshold effects of climate on reproduction and survival, competition, predation, or density-dependent population cycling, and were undetectable using the current framework. Intra-annual associations between model variables may also be influential in developing a best fitting model, and should be examined in future studies.

Introduction

Hantavirus ecology and epidemiology

Hantavirus pulmonary syndrome was first identified North America in the spring and summer of 1993. Initial cases were clustered in the Four Corners region of the southwestern United States, where origins of the disease were traced to an unrecognized, directly transmissible virus later named Sin Nombre virus (SNV) (genus *Hantavirus*, family Bunyaviridae) (Schmaljohn and Hjelle 1997). SNV is transmitted to humans through inhalation of secretions and excretions from infected *Peromyscus* rodents, in particular the deer mouse (*Peromyscus maniculatus*) (Mills et al. 1997, Glass et al. 2002). Rodent-borne hantaviruses are well-known in Europe and Asia (Monroe et al. 1999), and have recently been identified in Argentina, Chile, and Paraguay (Mills and Childs 1998).

The 1993 HPS outbreak is attributed to atypical climatic conditions associated with the 1991-1992 El Niño Southern Oscillation (ENSO), including heavy spring and summer precipitation in 1991/1992 and a mild winter in 1992 (Parmenter et al. 1999, Hjelle and Glass 2000). Spring 1993 *Peromyscus* populations in the southwest showed significantly greater densities than in previous years, suggesting that the 1991-1992 ENSO event was a causal factor in the emergence of the disease cluster in the southwestern United States. A trophic cascade hypothesis is proposed as a likely explanation for the timing and location of the outbreak (Parmenter et al. 1999, Glass et al. 2000, Glass et al. 2002, Zizi et al. 2002).

Trophic cascades are interactions between organisms from different levels within a food web (e.g. producers, consumers, and predators) that result in changes in abundance and biomass across trophic levels (Pace et al. 1999). In terrestrial systems primary level trophic cascades are initialized by precipitation, followed by an increase in ecosystem productivity (growth of grasses, seeds, leaves, nuts, and subsequently insects) stimulated by recharged soil moisture. Increased primary and secondary productivity and mild seasonal temperatures promote high rates of reproduction and survival in reservoir populations through extension of the reproductive period and favorable overwintering conditions (Abbott et al. 1999, Mills et al. 1999) (Figure 2.1). The trophic cascade hypothesis may explain inter- and intra-annual increases in *P. maniculatus* populations. In addition, trophic-cascade mitigated changes in reservoir population density may influence the presence of disease (seroprevalence) within populations through regulation of two epidemiological processes: rate of transmission and probability of infection (Figure 2.2).

Rate of hantavirus transmission is directly related to the proportion of susceptible individuals within a population: when this proportion is large the rate of disease transmission is high (Mills et al. 1999, Keeling and Gilligan 2000). A larger number of disease-susceptible individuals may be present within the population following the reproductive season, once those maternal antibodies that confer disease resistance to juvenile animals have been neutralized, or following population irruption events (Mills et al. 1999, Douglass et al. 2001).

Probability of infection is dependent on population density because identified mechanisms of disease transmission within reservoir populations are density-dependent. When populations are large and dense, greater frequencies of rodent-to-rodent contact increase the probability of virus transmission between susceptible individuals, through such behaviors as communal nesting and territorial aggression (Mills et al. 1999, Root et al. 1999, Douglass et al. 2001, Ostfeld and Holt 2004). Although attempts to definitively link hantavirus prevalence with reservoir population density have been somewhat inconclusive (Douglass et al. 1996, Mills et al. 1997, Boone et al. 1998, Douglass et al. 2001), a recent study found that antibody-positive deer mice were far more likely to be present at high-density rather than low density sites (Boone et al. 1998) suggesting that site population density exerts some control over population seroprevalence. Applying the trophic cascade hypothesis as the basis for predicting disease risk in human populations suggests that increased precipitation and biotic productivity triggers establishment of large reservoir populations, with high rates of disease transmission and probability of infection. Such conditions maximize the probability of encounters between humans and infected rodents.

Through July 6, 2005, 396 cases of HPS have been reported in 32 states within the continental US (CDC 2006) (Figure 2.3). The persistence of this disease beyond the atypical conditions following the 1991-1992 ENSO suggests that ongoing processes affect disease risk. Expansion of urban and agricultural areas may significantly increase contact between human populations and

disease vectors. Predicted increases in global temperature and precipitation (Jackson, 1995; McMichael and Haines, 1997) may trigger large-scale, long-term trophic cascades that increase rodent population density and dispersal, significantly increasing risk of disease. Human health concerns extend beyond HPS – increases in rodent populations have been correlated with a number of other diseases, including Lyme disease, plague, nephropathia epidemiea, myocarditis, Guillian-Barre syndrome, and insulin-dependent diabetes mellitus (Parmenter et al. 1999, Ostfeld and Holt 2004, Collinge et al. 2005).

The deer mouse is one of the most common and widely distributed rodents in North America (Hooper 1968): deer mice infected with SNV are present in all states within the species' range except Alaska (Mills et al. 1997). The presence of SNV throughout the maximum geographic range of the species suggests that the potential for endemic human disease exists wherever populations of deer mice are found, although a non-uniform distribution of HPS cases within and across states suggests that environmental and epidemiological factors mitigate disease transmission and incidence. Identification of these factors is critical to the development of a predictive model for disease risk in humans.

Hantavirus modeling

Disease is a product of interactions among disease agents, disease hosts, and the environment (Duncan 1992). Sin Nombre virus, the main etiologic agent of HPS, and *Peromyscus maniculatus*, its primary reservoir (Mills et al. 1997),

are identified as disease agent and host, respectively; the environment is the biotic and abiotic context in which the disease host resides (Figure 2.4). Disease incidence and survival rates in human populations are further influenced by demographic and epidemiological variables such as age, gender, occupation, medical history, and access to health care (CDC 2002), and residence in rural areas may differentially account for disease exposure (Douglass et al. 2005). A model framework that accounts for human behaviors as well as direct and indirect effects on reservoir species is extremely complex, and not therefore temporally or spatially generalizable. To create as broadly applicable a model as possible it is assumed here that risk of human hantavirus exposure is directly proportional to the probability of contact with hantavirus-infected rodents (Morse 1995, Mills and Childs 1998, Zizi et al. 2002).

Thus far no successful generalized predictive model for HPS has been developed, and as noted by Mills et al. (1999) "When the environmental variables associated with increasing reservoir population densities are identified and quantified, a key component of a predictive model of human risk will be in place." Douglass et al. (2001) suggest that predictive models for SNV-related disease may be developed by relating changes in reservoir population to fluctuations in plant productivity. Although previous studies have quantified some relationships between rodent population density and landscape and climate variables (MacCracken et al. 1984, Brown and Heske 1990, Parmenter et al. 1993, Parmenter and Vigil 1993, Meserve et al. 1995, Graham and Chomel 1997, Mills et al. 1997, Mills and Childs 1998, Abbott et al. 1999, Engelthaler et al. 1999,

Kuenzi et al. 1999, Lima et al. 1999a, Lima et al. 1999b, Mills et al. 1999a, Mills et al. 1999b, Parmenter et al. 1999b, Boone et al. 2000, Calisher et al. 2000, Ernest et al. 2000, Langlois et al. 2001, Peng et al. 2002), few studies been conducted in a manner useful for broad-scale modeling and prediction.

Remote Sensing

The GPP data used in this study were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS), flown onboard the NASA Earth Observing System Terra satellite. This sensor may prove to be a more powerful and effective terrestrial monitor than other remote sensors (Glass et al. 2000, Glass et al. 2002) because of its enhanced radiometric, spectral, and geometric qualities (Friedl et al. 2002). The MODIS GPP product, although partially dependent on spectral reflectance for its input data stream, also incorporates daily bioclimatology and carbon cycling logic in its vegetation productivity estimation. The disadvantage of MODIS GPP is its relatively coarse, 1-kilometer spatial resolution; the tradeoff is its short 8-day compositing period, near-real-time data availability, and rigorous quality control (Zhao et al. 2005).

Recent studies have listed resource abundance, temperature, and precipitation as the ultimate environmental factors that influence the temporal and spatial dynamics of *Peromyscus* populations (Abbott et al. 1999, Mills et al. 1999), and because the MODIS GPP algorithm uses temperature and precipitation as part of its estimation the GPP product accounts for these ultimate drivers in a single data set. Thus far no study has examined the relationship

between rodent density and MODIS GPP; therefore the predictive capabilities of the MODIS product for hantavirus modeling have not previously been evaluated. By describing and quantifying the relationships between reservoir population density and resource abundance, estimated using MODIS GPP, I provided a method for predicting human health risk that can be implemented over short time scales, broad spatial scales, and a variety of vegetation types, using a single input data set.

Methods

Rodents

I used longitudinal trapping data for *Peromyscus maniculatus* from live-trapping grids at three sites in Montana to evaluate the association between vegetation gross primary productivity (GPP) and rodent population density and population rate of change. These sites are maintained as long-term study areas for monitoring changes in hantavirus reservoir population density and associated environmental variability (Douglass et al. 2001). These and other longitudinal mark-recapture studies of *Peromyscus* rodents have been established by a number of independent researchers in a variety of ecosystems within the United States (Abbott et al. 1999, Calisher et al. 1999, Kuenzi et al. 1999) to provide information on host-virus associations and patterns of infection by age, sex, ecosystem, geographic region, season, and species. Mark-recapture methods are useful for tracking population responses to environmental and climatic variation, and assessing population natality and mortality.

I obtained monthly *P. maniculatus* population data for three rodent trapping sites: Cascade, Cutbank, and Gold Creek (Figure 2.5). Site elevation ranged from about 1200 meters to 1600 meters, and site vegetation was composed of grasslands (Cascade and Cutbank) or mixed Ponderosa pine-Douglas-fir forest (Gold Creek) (Table 2.1). Rodents were live-trapped at three 1-ha grids per site for 12 months (Cascade) or six months (Cutbank, Gold Creek) annually. Grids consisted of 10-trap by 10-trap arrays of 100 total Sherman live-capture traps spaced at 10 meter intervals. A comprehensive description of trapping protocols and methods used across study sites can be found in Douglass et al. (2001). I used only May-October capture data for all sites to allow for between-site comparisons, and because it has been observed that snow cover during winter months can interfere with trapping efforts, resulting in spurious population counts for those months (Douglass et al. 2001).

Population data were available as minimum number alive (MNA), produced using the enumeration technique (Chitty and Phipps 1966). The MNA metric accounts for the current monthly population as the sum of all animals captured during that period, corrected by the number of captures from the preceding and subsequent trapping periods; this correction is propagated through the dataset for a more robust assessment of population density. I averaged *P. maniculatus* MNA for the three grids per site to produce a monthly site average MNA. Averaging captures across grids increases my sampling size, and expands the rodent trapping scheme to a spatial scale more appropriate for analysis with remotely sensed data. I summed MNA data for each year to obtain

an annual rodent density for each trapping site. Although continuous trapping data are available from mid-1994 I focus on the period of 2000 through 2004, the temporal range for which both MODIS GPP and reservoir population data were available.

Bioclimatology

The standard MODIS GPP algorithm (MOD17A2) incorporates coarse-resolution 1.00° x 1.25° daily meteorology from the Data Assimilation Office (DAO) as its input bioclimatology (Running et al. 2004, Zhao et al. 2005). Coarse-scale meteorological input has been shown to work well across broad spatial scales, but may cause over- or under-estimation of GPP at small spatial scales (Running et al. 2004, Zhao et al. 2005). To reduce error in GPP estimations I substituted site-specific daily temperature and precipitation from ground-based weather stations, and humidity and radiation estimates from a climate simulation model.

Site-specific meteorology data were obtained from the National Climatic Data Center (NCDC, Ashville, North Carolina), from the nearest suitable weather station to each rodent trapping site. The NCDC is the world's largest weather data archive, and includes long-term historical data inventories from more than 30,000 stations globally. These data sets are available in digital ASCII format and can be ordered electronically via the web at hourly, daily, monthly, or annual time scales[1]. I acquired daily minimum temperature (Tmin), daily maximum

[1] http://www.ncdc.noaa.gov/oa/ncdc.html

temperature (Tmax), and daily precipitation for 2000 through 2004. A limited number of missing observations were gap-filled using linear interpolation.

The NCDC data provided the basis for the bioclimatology input to the MOD17A2 algorithm, which requires the following full set of input meteorology variables: Tmin, average temperature (Tavg), daytime average temperature (Tday), daily actual vapor pressure (AVP), daytime average vapor pressure deficit (VPD), and total shortwave radiation (SWRad) (Zhao et al. 2005). I used a climate simulation model to derive bioclimatology variables not directly available from ground-based weather stations, and to adjust for differences in elevation between weather stations and rodent trapping sites, that may affect vegetation physiology.

The Mountain Climate Simulator (MT-CLIM) was used to estimate the parameters Tday, VPD, and SWrad. The MT-CLIM model spatially extrapolates "base" meteorological conditions (input data) to a "site" location and derives additional site-specific meteorology from those input data (Glassy and Running 1994). Base locations were the weather stations that provided input meteorology, and sites were rodent trapping sites. Elevation and latitude were averaged across the three trapping grids per site and used in MT-CLIM initialization files. The simulation model output provides the required input variables for the MOD17A2 algorithm and 8-day GPP estimation. The MT-CLIM source code and documentation can be downloaded from the Numerical Terradynamic Simulation Group at the University of Montana[2].

[2] http://www.ntsg.umt.edu/

Remote Sensing

Primary productivity is the rate at which light energy is converted to plant biomass. Gross primary productivity (GPP) is the sum total of the converted energy, without accounting for plant respiration costs. Increases in atmospheric CO_2 and global climate change may alter GPP over large areas (Running et al. 2000), and incremental spatial and temporal variability may be caused by intra- or inter-annual fluctuations in temperature, precipitation, and incident radiation. Additionally, changes in land cover resulting from deforestation, urbanization, agriculture, logging, forest fires, etc. may alter terrestrial productivity at multiple scales (Running et al. 2004). Landscape sensitivity to variability in its abiotic and biotic context suggests that primary productivity estimates should be made frequently and across broad scales in order to capture ongoing dynamics. Remote sensors provide the means by which such estimates are made.

Annual and 8-day composited vegetation productivity data (MOD17 products) are available from the Moderate Resolution Imaging Spectroradiometer (MODIS), onboard NASA's Earth Observing System (EOS) Terra (launch date 1999) and Aqua (launch date 2002) satellites. The MOD17 algorithm produces two sub-products: MOD17A2, with 8-day composite GPP, net photosynthesis, and quality control (QC) and MOD17A3, with annual net primary productivity (NPP) and QC. The MODIS sensor is the first of its kind to offer near-real-time, regular vegetation monitoring, produced at a 1-kilometer spatial resolution. I used the MOD17A2 algorithm to derive vegetation productivity estimates over the longitudinal study sites.

The MOD17A2 algorithm uses a number of inputs in its GPP estimation, including fraction of photosynthetically active solar radiation (fPAR) absorbed by vegetation canopies, SWRad, Tmin, VPD, and a maximum radiation conversion efficiency (ε_{max}), scaled using Tmin and VPD:

$$GPP = (SWRad * 0.45 * fPAR) *(\varepsilon_{max} * [mTmin] [mVPD]).$$

Under the standard MODIS GPP data stream (Figure 2.6) fPAR is provided by the MOD15 algorithm (Justice et al. 2002) and SWRad, Tmin, and VPD are acquired from the DAO global meteorology data set. I substituted NCDC site meteorology for DAO meteorology, and calculate 8-day MODIS GPP for 2000 through 2004 using MOD17A2 logic (Figure 2.7). For a detailed discussion of the MOD17 algorithm see Zhao et al. (2005) and Heinsch, Zhao et al. (in press).

The MODIS GPP product is biome-specific, in that a land cover classification scheme is used to determine correct values of ε_{max} for each pixel. Land cover class is derived from the MODIS Land Cover product, MOD12Q1, which provides global land cover at 1-kilometer spatial resolution, updated on an annual basis (Friedl et al. 2002). The MOD17 algorithm uses Boston University's UMD classification scheme to classify land cover as one of 15 types (Hansen et al. 2000) (Figure 2.5).

I obtained MODIS 8-day GPP for 3-kilometer x 3-kilometer matrices centered over the midpoint of each 1-ha rodent trapping grid. The 9 km^2 footprint accounts for geolocation errors of the sensor, which may offset the pixel of interest by up to 150 meters for any given swath (Wolfe et al. 2002). I averaged GPP over those pixels in the matrix for which MOD12Q1 UMD land cover class

corresponded to land cover reported on the ground for each rodent trapping grid. No fewer than three pixels were excluded from the matrix average for any of the nine trapping grids used in our analysis, and for two of the grids no pixels were excluded (Table 2.1). I scaled the initial grid-based average GPP estimations to site level data by averaging the 8-day GPP observations across trapping grids (three per site), gap-filled to create total monthly site GPP, and summed monthly GPP to obtain total annual GPP per site. It should be noted that at the time of this study standard product MODIS GPP data were not intercomparable pre- and post-2004 because of compatibility issues in DAO input meteorology across those years. The use of site-specific, weather station-derived input meteorology allowed for inter-annual comparison.

Statistical Analysis

For every year in the study (2000-2004) there were data for precipitation, MODIS GPP, and *P. maniculatus* MNA. Annual precipitation data were the sum of precipitation in centimeters recorded daily per year at weather stations associated with each site, MODIS GPP were the total amount of carbon in grams fixed per year at each site, and MNA were the average site deer mouse density per year. The analyses described below were first performed on data from 2000-2003; subsequently data from 2004 were added and separate analyses was conducted.

All correlation analyses in this study were done using the Pearson product-moment correlation (*r*) procedure in SPSS (SPSS 1999). The Pearson

correlation was used to measure the association among precipitation, MODIS GPP and MNA at each longitudinal trapping site to determine whether these data are related in the manner suggested by the trophic cascade. Correlation analysis is used to test whether variables are interdependent or covarying, without any assumptions about dependence or causality (Sokal and Rolf 1995).

The Pearson framework used here tested for temporal (within-site) correlations and spatial (between-site) correlations. Within-site correlations are those expected under a trophic cascade scenario, which proposes a dependent relationship among precipitation, vegetation abundance, and rodent abundance. If the trophic cascade hypothesis adequately explains patterns in rodent abundance at the Montana study sites, within-site correlations among precipitation, vegetation abundance, and rodent density should be significant and positive, as shown using solid arrows in the path diagram in Figure 2.8.

Between-site correlations were tested to determine whether there is regional spatial synchrony among precipitation, MODIS GPP, or MNA. Spatial synchrony in rodent populations has been noted by a number of researchers (Korpimaki and Krebs 1996), and if present might suggest that more complex dynamics beyond site-level vegetation abundance regulate populations at the Montana study sites. The between-site correlations shown as dashed lines in Figure 2.8 should be significant and positive if there is a high degree of spatial correlation between sites, or if the sites are not spatially independent. In particular, positive correlations in MNA between the two grassland sites

(Cascade and Cutbank) could indicate a high degree of dependence on vegetation type as a factor in determining rodent population density.

Although correlations were considered significant at $p \leq 0.05$, I was interested in overall patterns of association between variables and sites, and between pre- and post-2004 data sets even when the outcome fell outside of this presumed level of statistical significance. Such results provide information on the scale of the dominant ecological processes that influence population dynamics of reservoir species.

Results

Patterns in rodent abundance

The May-October *P. maniculatus* population counts for the trapping period of record (1994-2004) were 38% and 60% higher at the Cascade site than the Cutbank or Gold Creek sites (n = 4.259, 2,639, and 1,692 total captures respectively). Deer mouse distribution in southeastern Montana has been positively related to the presence of several types of grasses, and deer mice abundance is also correlated with areas of grass cover (MacCracken et al. 1984). As grasses are the dominant vegetation type at the Cascade and Cutbank sites it is logical that these sites would have the highest *P. maniculatus* population density of those included in this analysis.

Much of the significant gain in rodent population density at the Cascade site occurred in 2002 and 2003, during which period the total site number of captures (summed across the three trapping grids) was only slightly lower than

for combined nine year trapping effort preceding and following those years (Figure 2.9). This period corresponds to the years for which the Cascade site *P. maniculatus* population exhibited significantly different patterns in rodent density than those observed for the Cutbank and Gold Creek sites. From 1994 through 2002 patterns in inter-annual population density between sites appeared fairly well synchronized, although the absolute population density between sites varied (Figure 2.10).

Temporal correlations

2000-2003 data: Temporal correlations are within-site linear relationships among model variables: precipitation, GPP, and MNA. Annual *P. maniculatus* population density (MNA) was plotted against MODIS GPP first for 2000 through 2003, the period for which MODIS GPP data were initially available, and subsequently for 2000 through 2004. Scatter plots from the 2000-2003 dataset showed a linear-appearing relationship between MNA and GPP across all three study sites (Figure 2.11). In addition, line plots of GPP and MNA produced regularly varying periods (intervals between successive density peaks) that suggest that these variables covary (Figure 2.12). I used the Pearson product-moment correlation to test for covarying linear relationships between GPP and MNA, shown as pathways b_1, b_2, and b_3 in the diagram in Figure 2.8. Although the Cutbank site produced the only significant positive association between annual MNA and MODIS GPP ($r = 0.975$, $df = 3$, $p < .05$), correlation coefficients for the Cascade and Gold Creek sites were high enough ($r = 0.89$ and 0.84,

respectively) to suggest a potential underlying relationship between MNA and MODIS GPP (Table 2.2a); furthermore, with the small sample size (n = 4) non-significant p-values are not uncommon.

For the 2000-2003 period precipitation and MODIS GPP (pathways a_1, a_2, and a_3) and precipitation and MNA (pathways c_1, c_2, and c_3) were significantly correlated at the Cascade site only (Table 2.2a). At the Cutbank and Gold Creek sites there were negative, non-significant correlations between precipitation and GPP and precipitation and MNA.

2000-2004 data: Comparisons of MODIS GPP and MNA across the three study sites using 2000-2004 data produced markedly different results from the 2000-2003 analysis. Although the data set retained a marginally significant correlation between MNA and GPP at the Cutbank site, correlation coefficients at all sites were much lower than those obtained using 2000-2003 data (Table 2.2b). Scatter plots show that the 2004 MNA-GPP data point falls well outside of the linear distribution defined by the first four years of site data (Figure 2.11), and line plots of 2000-2004 MODIS GPP and MNA indicated that in 2004 at all sites GPP increased while rodent density decreased (Figure 2.12). The addition of this single data point effectively reduces the explanatory power of annual trophic cascade effects as drivers of rodent populations across the full five-year data set, because under a trophic cascade scenario the high observed vegetation productivity in 2004 should have been accompanied by higher numbers of rodents at the study sites.

The within-site temporal correlations for precipitation-GPP and precipitation-MNA were much the same as those obtained using 2000-2003 data. With the exception of a significant, positive correlation between precipitation and MODIS GPP found at the Cascade site, all sites showed non-significant results for precipitation-GPP and precipitation-MNA correlations. There was no obvious association between precipitation and MODIS GPP at the Cutbank and Gold Creek sites, although there was graphical evidence of the precipitation-GPP correlation at the Cascade site (Figure 2.13).

Spatial correlations

Spatial correlations were between-site linear relationships between precipitation, GPP, and MNA. Similar patterns in between-site correlations were observed for 2000-2003 data versus 2000-2004 data (Tables 2.3a, 2.3b). I found positive but marginally significant correlations in precipitation between the Cutbank and Gold Creek sites, significant and positive correlations in MODIS GPP at the Cascade and Gold Creek sites, and positive, marginally significant correlations in MNA at the Cascade and Gold Creek sites.

Discussion

In general the results indicated by this analysis suggest that trophic cascades alone are insufficient to explain patterns in rodent density at the three study sites. Although the trophic cascade hypothesis has been forwarded to explain rodent population irruptions in the southwestern United States

(Parmenter et al. 1999, Glass et al. 2000, Glass et al. 2002) those studies were conducted in ecosystems where water is a limiting factor in plant growth. Monsoonal precipitation patterns, common across the southwestern United States, have been found to be strong drivers of biotic cascades. In contrast, at the Montana study sites water may not be similarly limiting and precipitation patterns are not monsoon-driven, which may alter the sensitivity of vegetation communities and rodent populations to changes in timing and amount of rainfall. Based on the results of this analysis, the application of the trophic cascade hypothesis as a universal, broad-scale explanation for *P. maniculatus* population density and HPS risk is incorrect.

The original analysis using 2000-2003 data pointed toward interdependence between vegetation abundance and rodent density at the three study sites, but the 2000-2004 Pearson product-moment correlations indicated that in 2004 these variables were significantly decoupled. Predictions using the initial four year data set seem fairly straightforward: that increases in annual vegetation primary production are associated with increases in annual *P. maniculatus* density. The presence of these associations across diverse biome types suggested that the underlying population processes proposed by the model diagram in Figure 2.2 can be captured using the MODIS GPP product with substituted site-specific meteorology, and that trophic cascaded may be useful explanatory mechanisms for peaks in rodent density in Montana ecosystems. However, when 2004 data were added to the analysis the correlation coefficients and scatter plot distributions for annual site average MODIS MNA and GPP

changed significantly, such that there was no measurable association between these two variables for the Cascade and Gold Creek sites and a marginally significant association at the Cutbank site. Data for this period showed that although site average annual MNA decreased by 80% at Cascade, 14% at Cutbank, and 2% at Gold Creek from 2003 to 2004, in 2004 vegetation productivity achieved a five-year maximum at each of the three sites. These results were dramatically different from those expected under a trophic cascade scenario, suggesting that other factors influence population density and/or population cycles in Montana ecosystems. Microtine rodents have been shown to exhibit normal population cycles of three to five years (Krebs and Myers 1974, William J. Lidicker 1988, Korpimaki and Krebs 1996), although no definitive explanations for the periodicity or amplitude of these cycles have been forwarded. Although in general competition and predation have been cited as the most influential biotic factors on the spatial and temporal distribution of species (Huito et al. 2004), granivorous rodents such as *Peromyscus* spp. are most likely mainly resource-limited rather than predator controlled (Ernest et al. 2000).

Surprisingly, the only significant correlation between annual site average MODIS GPP and precipitation was found for the Cascade site. Because the MODIS GPP data set incorporates site climatology, including precipitation, into its vegetation production estimations, I expected a significant correlation between GPP and precipitation at all of the study sites. Possible explanations for the results are that a significant portion of the annual sum precipitation at Cutbank

and Gold Creek fell outside the growing season and therefore did not contribute directly to plant growth, or that weather station data did not accurately reflect site precipitation patterns because of distance from the study sites and therefore were poorly correlated with vegetation productivity.

Between-site correlations were non-significant for the precipitation and MNA pathways tested in the analysis, suggesting that there is no spatial interdependence in these variables. However, the marginally significant and positive covariation in GPP between Cascade and Gold Creek indicated that there may be some spatial synchrony in vegetation production between these two sites. Consideration of MODIS GPP algorithm inputs indicated that this may exist as the result of similar patterns in minimum and maximum temperature between the two sites, because other inputs (precipitation, fPAR) vary between the two sites.

The relevance of this study for human health is twofold. First, I demonstrated that although trophic cascades may be used to predict rodent population irruptions in the southwestern United States, similar methodologies are not always suitable in more northerly ecosystems. Based on my results I suggest that the relationship between vegetation productivity and rodent density is complex and non-linear, and may be dependent on inter- or intra-annual time lags. Although as yet unidentified, there are likely a number of extrinsic (environmental) and intrinsic (population) factors that influence variability in rodent population density. Assuming a linear model for development of high-density rodent populations neglects likely causal factors, and may lead to

oversimplified and erroneous predictive models for HPS outbreaks. Although my 2000-2003 data showed that vegetation abundance and rodent density can covary, there are no definitive recommendations for risk prevention that can be concluded from these results.

Second, my results suggested that the MODIS GPP product is a useful input variable for future predictive models. Although remotely sensed data are typically incorporated into large-scale spatial estimations of disease risk rather than point-based ones, the method presented here for extracting site-level GPP estimations seems to work well. The substitution of site-specific precipitation and temperature for the coarse-scale, gridded meteorology used in the standard MODIS algorithm creates a more site-specific product that is better-suited for analysis at microhabitat scales than the standard product.

Conclusions

Although vegetation productivity is hypothesized to be an important driver for rodent population density, my data and others' suggest that additional extrinsic or intrinsic processes regulate reservoir populations (MacCracken et al. 1984, Abbott et al. 1999, Mills et al. 1999, Calisher et al. 2000). Potential influences include predation, competition with other rodent species, changes in microhabitat composition, and fluctuations in temperature and precipitation that may have short-term positive or negative influences on reproduction and survival.

Statistical analysis of the MODIS GPP and MNA data sets produced mixed results. Trophic cascades, widely accepted in the southwestern United

States as the main mechanism by which deer mouse populations experience significant population irruptions (Parmenter et al. 1999, Glass et al. 2000, Yates et al. 2002), only partially explain inter-annual trends in MNA at the longitudinal trapping sites. Assuming that the MODIS GPP product accurately characterizes primary vegetation productivity and can therefore be used as a measure of resource abundance, it seems certain that additional factors beyond a trophic response influence development of high-density rodent populations.

Many researchers have recognized the need for models capable of predicting temporal and spatial risks of epidemics (Epstein 1999, Patz and Lindsay 1999, Myers et al. 2000, Rogers and Randolph 2000). Remote sensors can provide the timely and broad-scale inputs necessary for disease forecast models. This paper provides evidence that although reservoir population dynamics may be in part influenced by changes in resource abundance, additional factors exert influence over reservoir population growth. There is no evidence supported by the current study for a single, easily detectable, consistent catalyst for changes in rodent abundance, and further studies are required to more fully elucidate the causes of reservoir population variability. These may include intra-annual relationships among variables, predation and competition, and minimum and maximum thresholds in temperature, precipitation, resource abundance, and other landscape factors that influence the fecundity, mortality, distribution, and density of reservoir species. Inclusion of these processes into HPS forecast models requires more than statistical manipulation of existing data sets; field data collection should include detailed

weather and landscape data, predator and competitor species, and assessment of primary and secondary trophic resources.

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Table 2.1 Characteristics of rodent trapping grids including ground-reported (grid) land cover, UMD land cover class, and number of MODIS pixels used in the analysis.

Trapping Grid	Grid Land cover	UMD Land cover	Longitude	Latitude	Elevation (m)	MODIS Pixels Used[1]
Gold Creek 7	Douglas fir-Ponderosa pine	Evergreen needleleaf forest	-113.00750	46.51278	1655	9
Gold Creek 8	Thinned Douglas fir-Ponderosa pine	Evergreen needleleaf forest	-113.00806	46.51944	1618	9
Gold Creek 9	15-year old clearcut	Evergreen needleleaf forest	-113.00694	46.52250	1618	8
Cascade 10	Grasslands	Grasslands	-111.59361	46.98611	1438	6
Cascade 11	Grasslands	Grasslands	-111.58444	46.98972	1426	6
Cascade 11	Grasslands	Grasslands	-111.54722	46.99861	1420	6
Cutbank 13	Grasslands	Grasslands	-112.49444	48.96389	1321	7
Cutbank 14	Grasslands	Grasslands	-112.50944	48.97361	1277	7
Cutbank 15	Grasslands	Grasslands	-112.52722	48.98194	1237	7

[1] Out of a possible total of nine

Table 2.2a 2000-2003 within-site correlations in precipitation, GPP, and MNA.

Site	n	Precipitation-GPP	GPP-MNA	Precipitation-MNA
Cascade	4	0.91* (a_1)	0.89 (b_1)	0.99*** (c_1)
Cutbank	4	-0.29 (a_2)	0.98** (b_2)	-0.32 (c_2)
Gold Creek	4	-0.20 (a_3)	0.84 (b_3)	-0.55 (c_3)

Values from Pearson's correlation analysis: * P < .10, ** P < .05, *** P < .01

Table 2.2b 2000-2004 within-site correlations in precipitation, GPP, and MNA.

Site	n	Precipitation-GPP	GPP-MNA	Precipitation-MNA
Cascade	5	0.94** (a_1)	0.29 (b_1)	0.48 (c_1)
Cutbank	5	-0.11 (a_2)	0.81* (b_2)	-0.28 (c_2)
Gold Creek	5	0.11 (a_3)	0.29 (b_3)	-0.56 (c_3)

Values from Pearson's correlation analysis: * P < .10, ** P < .05, *** P < .01

Table 2.3a 2000-2003 between-site correlations in precipitation, GPP, and MNA.

Variable	n	Cascade-Cutbank	Cutbank-Gold Creek	Cascade-Gold Creek
Precipitation	4	0.50 $(a_{1,2})$	-0.91* $(a_{2,3})$	-0.12 $(a_{1,3})$
GPP	4	-0.03 $(b_{1,2})$	-0.41 $(b_{2,3})$	0.92** $(b_{1,3})$
MNA	4	0.46 $(c_{1,2})$	-0.05 $(c_{2,3})$	0.86 $(c_{1,3})$

Values from Pearson's correlation analysis: * P < .10, ** P < .05, *** P < .01

Table 2.3b 2000-2004 between-site correlations in precipitation, GPP, and MNA.

Variable	n	Cascade-Cutbank	Cutbank-Gold Creek	Cascade-Gold Creek
Precipitation	5	0.46 $(a_{1,2})$	-0.86* $(a_{2,3})$	0.05 $(a_{1,3})$
GPP	5	0.53 $(b_{1,2})$	0.55 $(b_{2,3})$	0.93** $(b_{1,3})$
MNA	5	0.26 $(c_{1,2})$	-0.10 $(c_{2,3})$	0.84* $(c_{1,3})$

Values from Pearson's correlation analysis: * P < .10, ** P < .05, *** P < .01

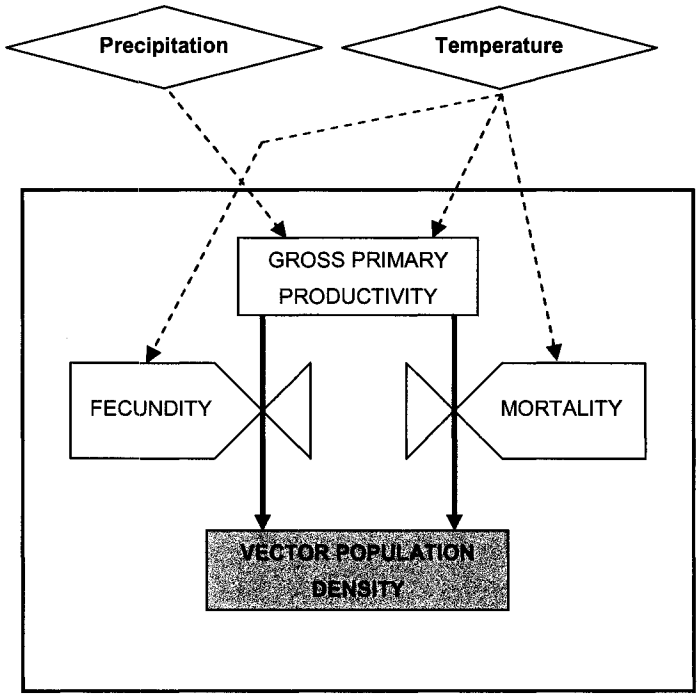

Figure 2.1 Conceptual model of the relationships among precipitation, temperature, vegetation productivity, and rodent populations predicted under the trophic cascade hypothesis.

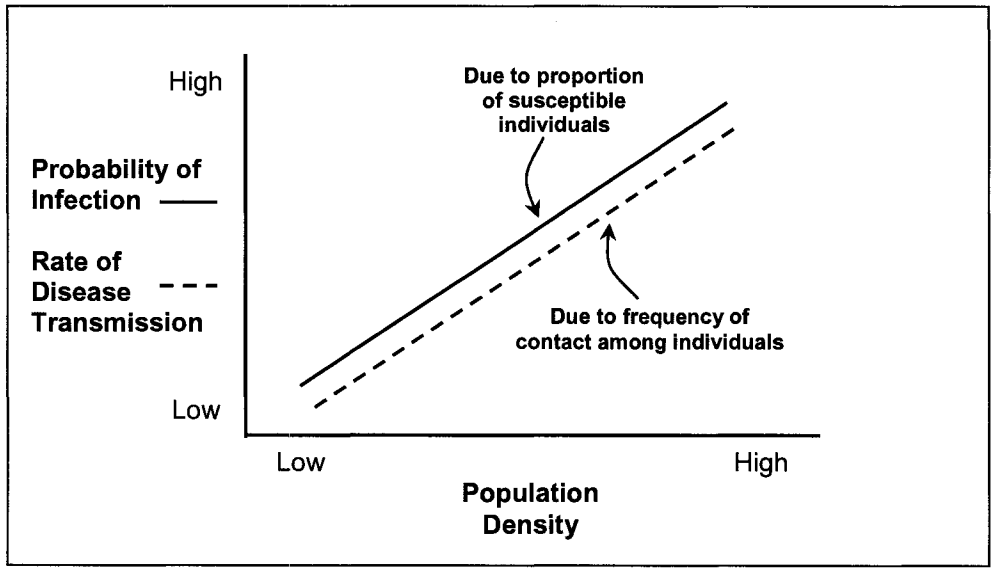

Figure 2.2 Relationship between reservoir population density, probability of infection, and rate of disease transmission. Probability of infection and rate of disease transmission are density-dependent processes regulated through the proportion of susceptible individuals in the population and frequency of contact among individuals.

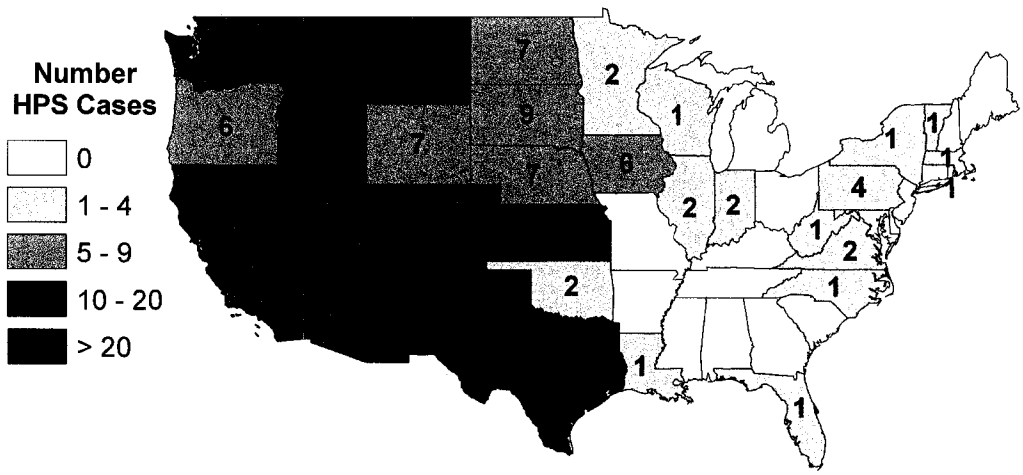

Figure 2.3 HPS cases by state of residence, July 2005. N = 396 in 32 states. Data are from the Centers for Disease Control and Prevention, Atlanta, GA.

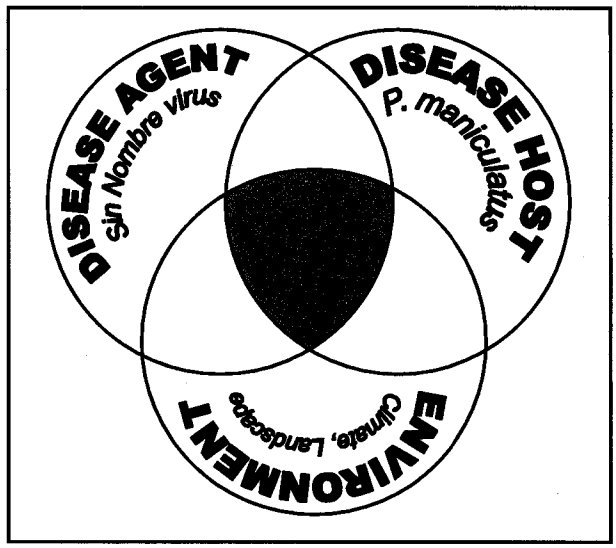

Figure 2.4 Disease agent-host-environment interactions.

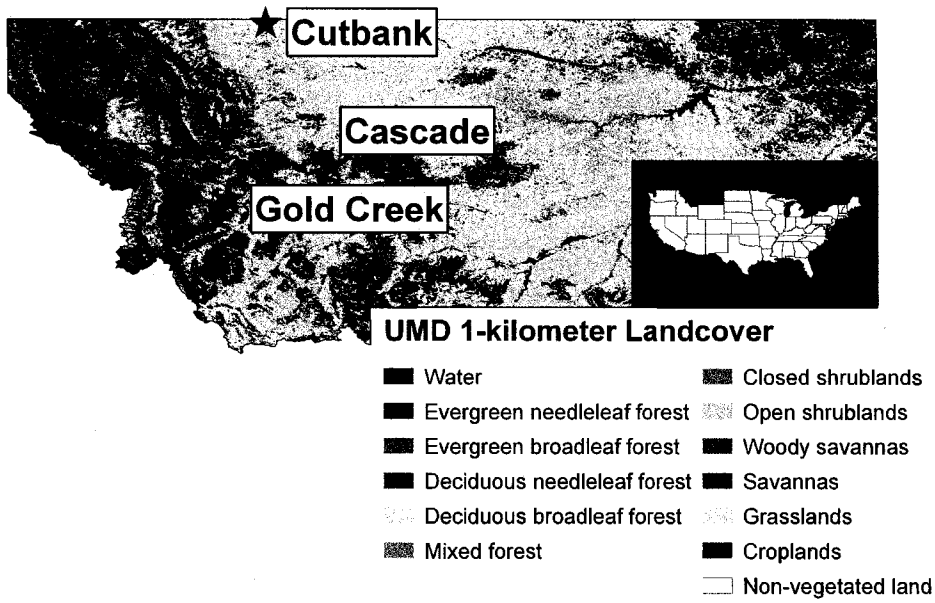

Figure 2.5 Montana longitudinal rodent trapping sites included in the analysis, with UMD 1-kilometer land cover classes used in the MOD17 algorithm.

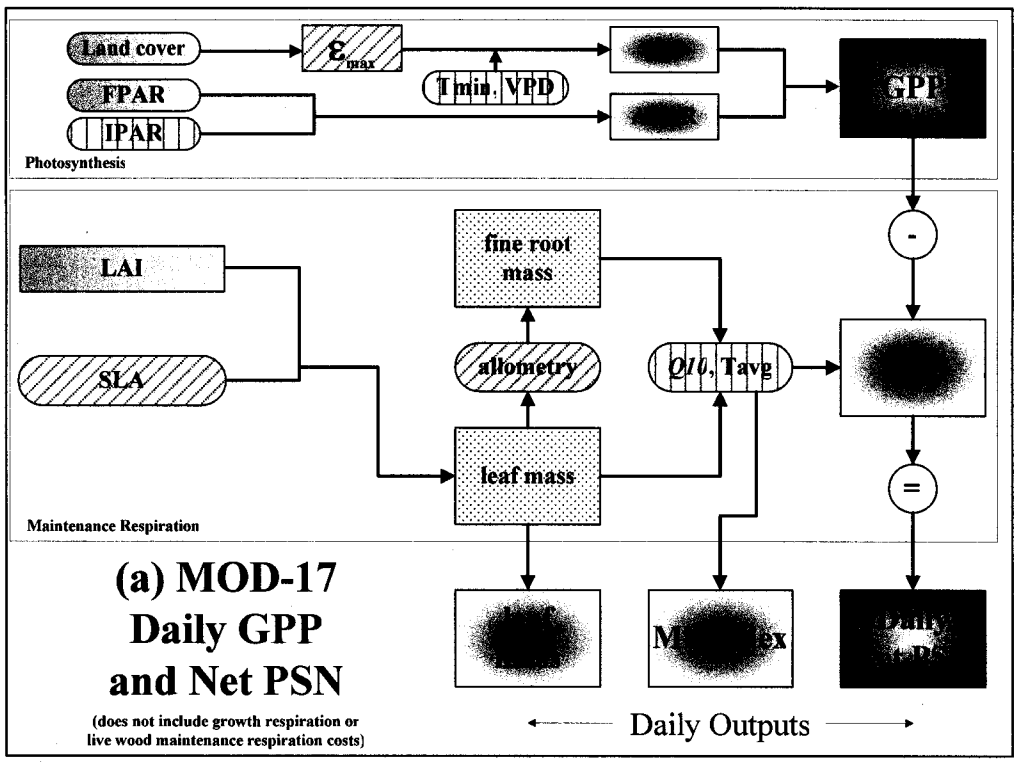

Figure 2.6 Standard product MODIS data stream. Key components: remote sensing inputs (land cover, LAI, FPAR); daily surface weather (IPAR = Incident Photosynthetically Active Radiation, Tmin = minimum daily temperature, Tavg = average daily temperature estimated from Tmin and Tmax, VPD = Vapor Pressure Deficit); lookup table with biome-specific coefficients generated from an ecosystem process model (ε_{max}, biometry, leaf longevity, respiration). To compute the MOD17 algorithm values of Tmin and VPD are used to attenuate biome-specific values of ε_{max} (radiation conversion efficiency) to produce ε. The APAR (Absorbed Photosynthetically Active Radiation) is calculated as APAR = IPAR * FPAR), and combined with ε to estimate daily GPP (Gross Primary Productivity) as GPP = ε * APAR.

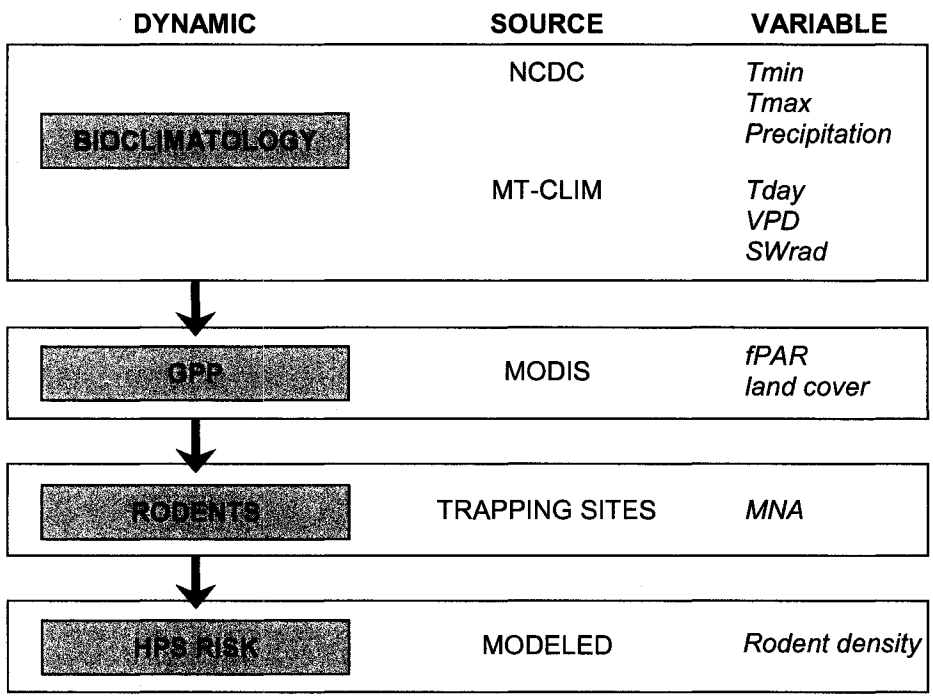

Figure 2.7 Model components with data sources and variables. The figure shows the steps used to process site-specific MODIS GPP, including incorporation of site meteorology and derivation of additional site parameters using the MT-CLIM model.

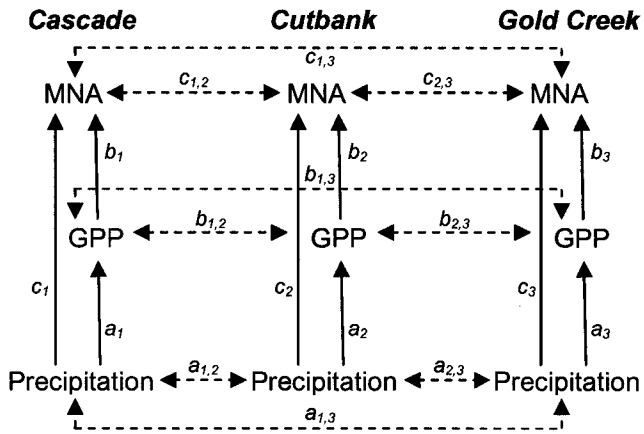

Figure 2.8 Path diagram of potential within- and between-site correlations in precipitation, GPP, and rodent density. Solid lines denote positive, significant correlations predicted by the trophic cascade hypothesis and dashed lines indicate between-site correlations expected under conditions of spatial interdependence.

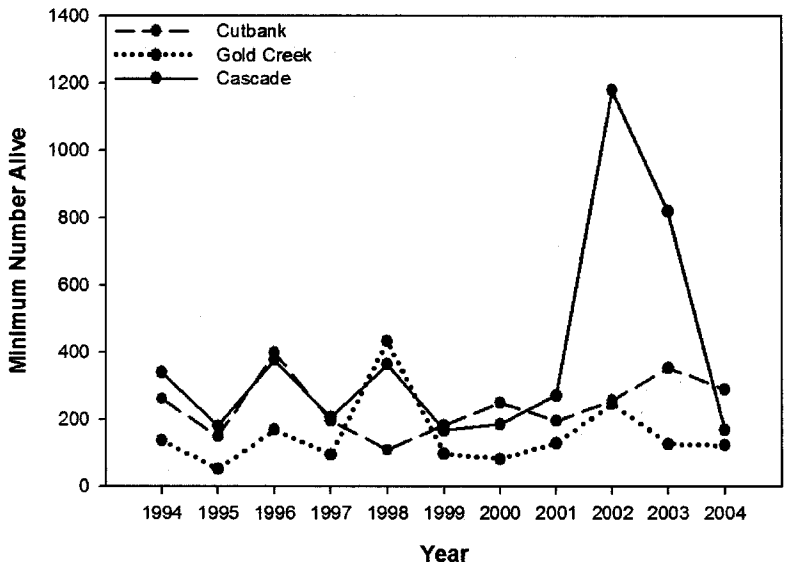

Figure 2.9 May-October *P. maniculatus* site total captures at the three Montana rodent trapping sites included in the analysis. Site data are summed monthly Minimum Number Alive across three grids per site, aggregated into an annual sum.

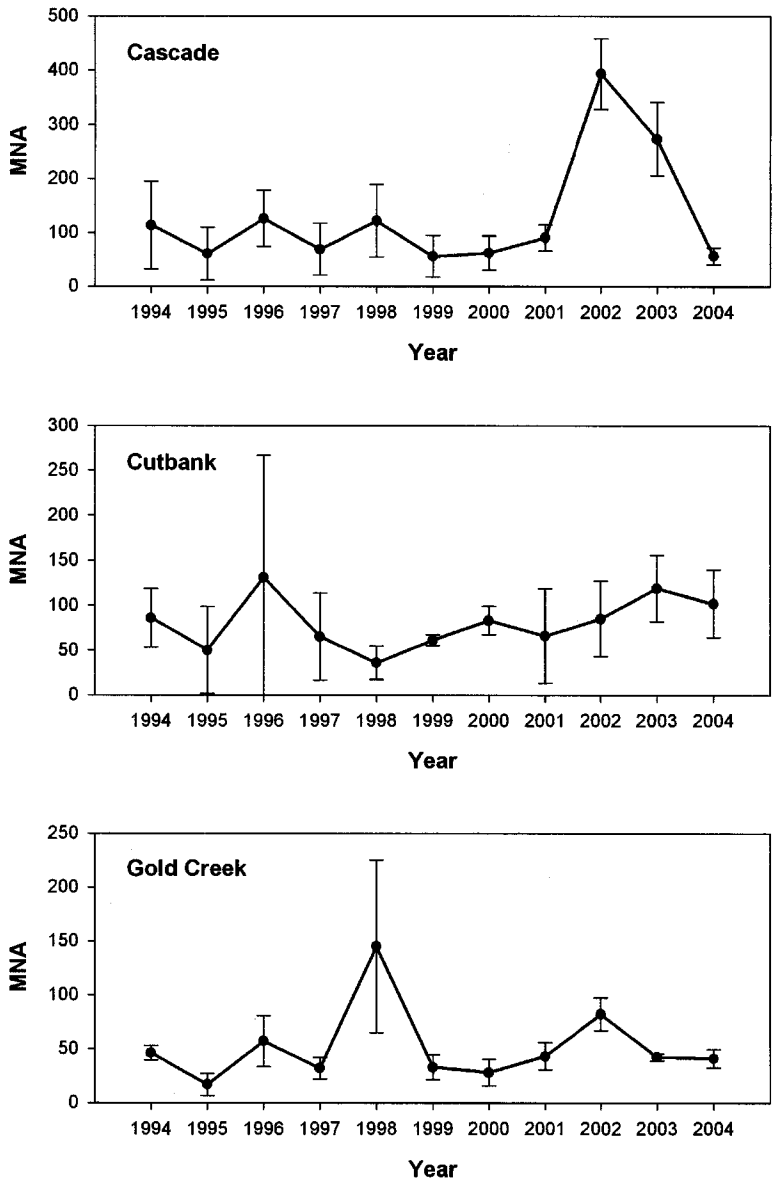

Figure 2.10 1994-2004 May-October *P. maniculatus* site average captures, calculated by averaging monthly Minimum Number Alive (MNA) across the three grids per site and summing the monthly site average MNA by year. Error bars are three grid mean ± 1 standard deviation.

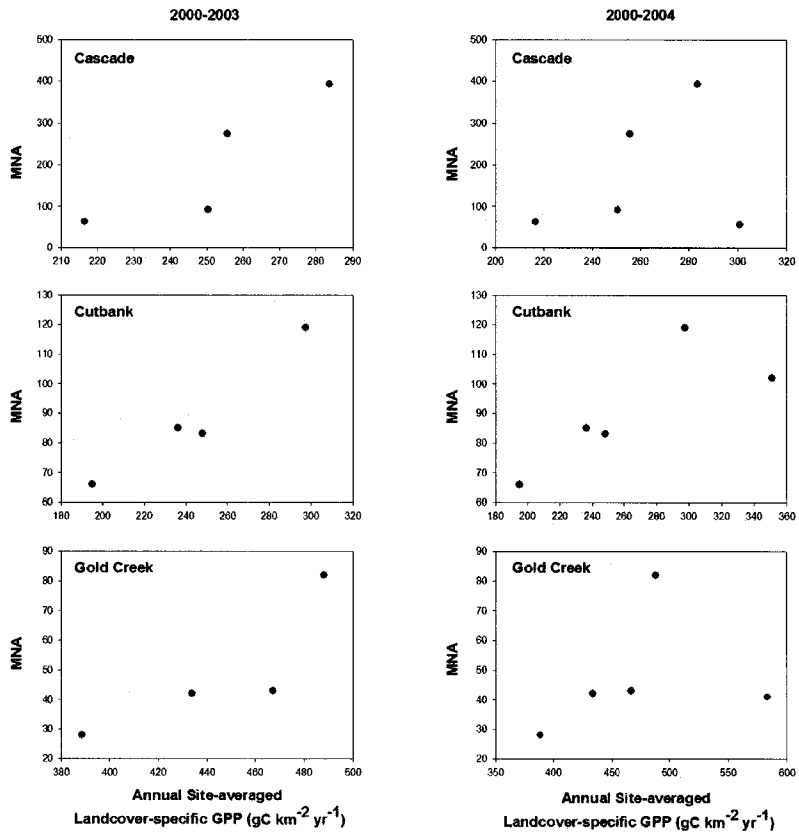

Figure 2.11 Site average Minimum Number Alive (MNA) versus MODIS GPP, 2000-2003 and 2000-2004.

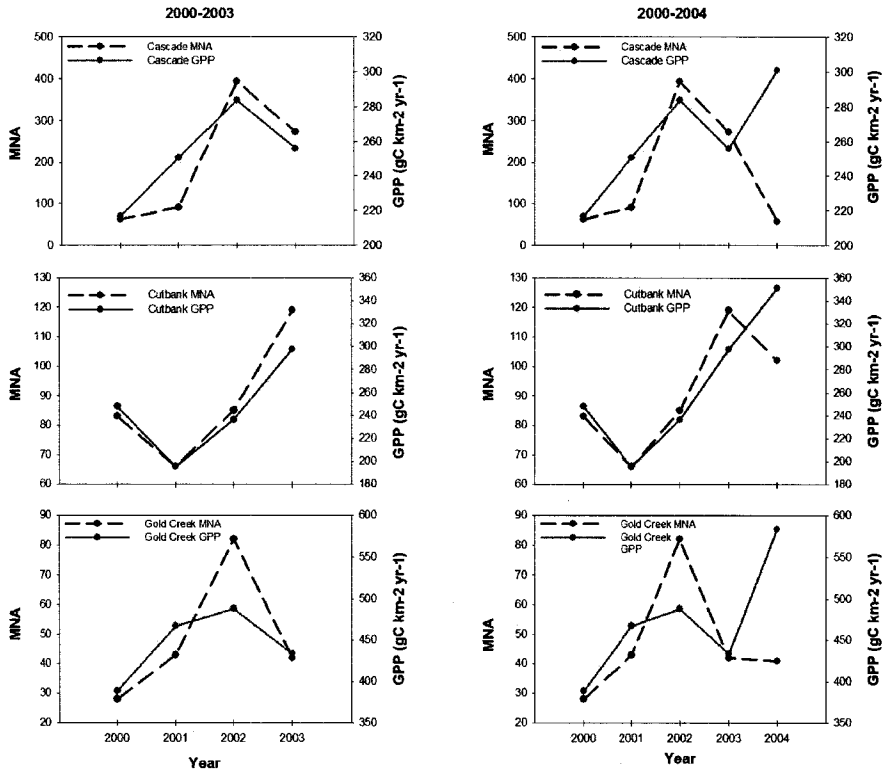

Figure 2.12 Site average Minimum Number Alive (MNA) and MODIS GPP, 2000-2003 and 2000-2004.

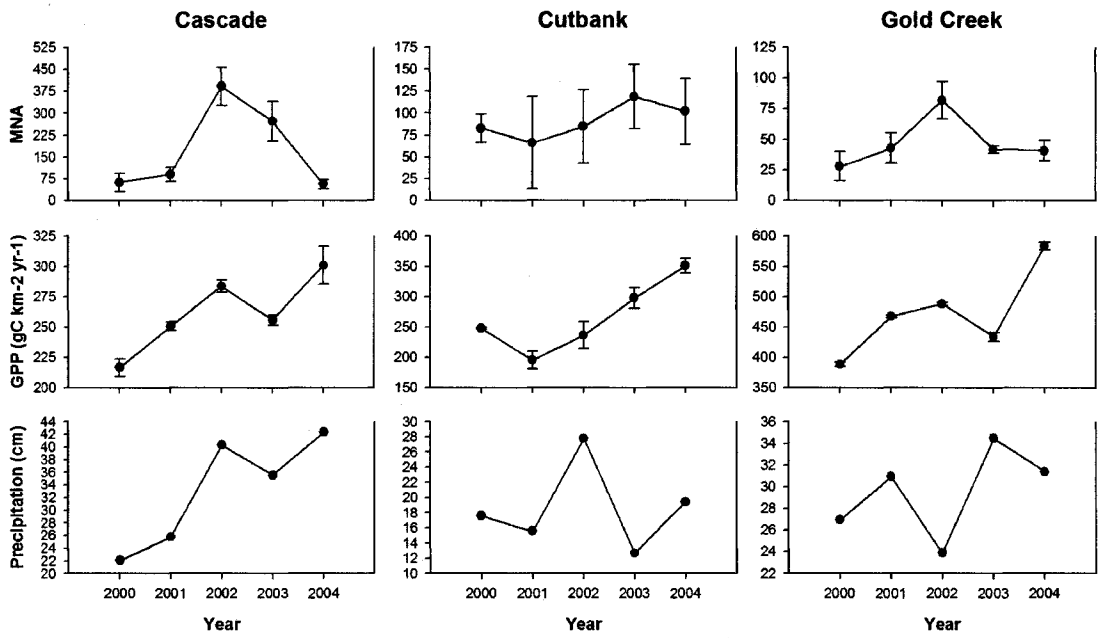

Figure 2.13 2000-2004 site average Minimum Number Alive (MNA), MODIS GPP, and precipitation. Error bars are three grid mean ± 1 standard deviation.

CHAPTER 3

POPULATION DYNAMICS OF SYLVAN AND PERIDOMESTIC DEER MICE RELATED TO RISK OF HANTAVIRUS PULMONARY SYNDROME

Abstract

Longitudinal rodent trapping data from sylvan and peridomestic sites in west central Montana were compared with vegetation productivity estimates from the Moderate Resolution Imaging Spectroradiometer (MODIS) remote sensor, to identify reservoir population and landscape characteristics associated with risk of hantavirus pulmonary syndrome (HPS) in human populations. Although almost all recorded HPS cases result from peridomestic exposure to infected rodents, most studies focus only on dynamics of sylvan populations. Alternatively, the current study examined interactions between sylvan and peridomestic populations and the environment that contribute to development of large, infective disease reservoir populations, implicated in transmission of hantavirus to humans. From 1997 through 2004 overall reservoir population size was greater at the sylvan site, although peridomestic seroprevalence was markedly higher. At annual and monthly time scales rodent density at the sylvan site was significantly and positively correlated with peridomestic population density and seroprevalence, suggesting that dispersal between sylvan and peridomestic habitats may facilitate disease transmission between populations. Vegetation gross primary productivity was positively associated with sylvan rodent population density, suggesting that variability in deer mouse populations is partially driven by a trophic cascade response; however, MODIS GPP explained only 12% of the variability in population density, indicating that other factors influence reservoir population dynamics.

Introduction

Hantavirus pulmonary syndrome (HPS) is an acute, often fatal illness clinically characterized by cardiorespiratory distress and bilateral interstitial pulmonary infiltrates, with associated fever, chills, muscle aches, headaches, and gastrointestinal symptoms (Wells et al. 1997, Young et al. 2000). Death from HPS occurs as the result of shock and cardiac complications caused by an overwhelming immunologic response to hantavirus antigens. HPS was first identified in North America during the spring and summer of 1993, in the Four Corners region of the southwestern United States. Origins of the disease were traced to a previously unrecognized, directly transmissible virus later named Sin Nombre virus (SNV) (genus *Hantavirus*, family Bunyaviridae) (Schmaljohn and Hjelle 1997). SNV is transmitted to humans through inhalation of secretions and excretions from infected *Peromyscus* rodents, in particular deer mice (*Peromyscus maniculatus*) (Mills et al. 1997, Glass et al. 2000). Through July 6, 2005, 396 cases of HPS have been reported in 32 states within the continental US, with an overall mortality rate of 36% (CDC 2006). Although HPS is a relatively rare disease, its high mortality rate underscores the importance of establishing effective methods for reducing risk of infection in human populations.

Current prevention methods for HPS include health education programs emphasizing symptom recognition, avoidance of risky activities, and rodent control measures for potentially affected households. Because epidemiological case-control studies found positive relationships between rodent abundance in and around homes and SNV infection in human populations (Armstrong et al.

1995, Childs et al. 1995, Zeitz et al. 1995), much attention has been paid to reducing rodent infestations in human structures. When combined with rodent proofing, trapping efforts have been shown to minimize the number of rodents potentially in contact with human populations (Glass et al. 1997, Douglass et al. 2003), although it has been noted that "intensive efforts to eliminate rodents over large land areas by trapping is neither feasible nor affordable" (Parmenter et al. 1993). In addition, rodent trapping in buildings without rodent proofing against means of ingress may result in subsequent recolonization by dispersing rodents, potentially increasing populations within buildings (Douglass et al. 2003). Rodent control activities may themselves be a significant source of disease: activities associated with HPS infection include trapping and handling of rodents in and around homes and cleaning of food storage areas and outbuildings (Armstrong et al. 1995, Zeitz et al. 1995).

Models to predict the timing of onset and spatial extent of HPS risk can be used to focus national and local public health resources on areas of special concern. Some such models have been developed to predict population dynamics of the hantavirus reservoir species, *P. maniculatus*, in sylvan environments, (Boone et al. 2000, Glass et al. 2000, Lidicker 2000, Langlois et al. 2001, Glass et al. 2002) but these models fail to fully account for the main, peridomestic context in which humans are exposed to SNV. Alternatively, the current project incorporated rodent population data from both sylvan and peridomestic sites in a framework that accounts for population growth, dispersal, and seroprevalence of the reservoir species.

Modeling hantavirus risk

Sylvan *P. maniculatus* populations are sensitive to changes in temperature, precipitation, and resource abundance (Abbott et al. 1999, Calisher et al. 1999, Engelthaler et al. 1999, Douglass et al. 2001). A trophic cascade, or escalation of productivity through primary and secondary pathways, is suggested as a likely catalyst for increased density of rodent populations (Parmenter et al. 1999, Glass et al. 2000, Glass et al. 2002, Zizi et al. 2002). A recent study correlated density of deer mice with vegetation gross primary production (GPP) at trapping sites across Montana, although results of this analysis were somewhat mixed (Loehman et al. in prep.). This study and others (Glass et al. 2000, Glass et al. 2002) demonstrate the application of remotely sensed (satellite) data for predicting population dynamics in SNV reservoir species. Thus far no study has incorporated satellite data into a peridomestic deer mouse population model, although such a predictive model would allow for disease risk assessment within urban or suburban settings, the true environments of exposure. In addition, although field and laboratory studies have been conducted to examine limited relationships between environmental variables, reservoir population density, and transmission of disease within populations (Childs et al. 1995, Glass et al. 1997, Mills et al. 1997, Boone et al. 1998, Abbott et al. 1999, Boone et al. 2000, Botten et al. 2000, Kuenzi et al. 2000, Douglass et al. 2001, Kuenzi et al. 2001, Botten et al. 2002, Brown and Ernest 2002, Douglass et al. 2003), no studies have accounted for environmental drivers,

population density, and seroprevalence of both peridomestic and sylvan rodents within a single integrated framework.

HPS risk areas are regions where potential for contact between humans and SNV-infected rodents is maximized. Conditions that affect the probability of contact between humans and SNV-infected rodents ultimately influence risk of HPS in human populations. Two main reservoir population parameters that are factors in human disease risk have been identified: prevalence of infection and population density (Calisher et al. 1999, Mills et al. 1999, Keeling and Gilligan 2000). There is interaction between these parameters such that when reservoir populations are densely concentrated, contact among individuals may increase transmission of disease, increasing overall disease prevalence within the population. Although attempts to definitively link hantavirus prevalence with reservoir population density have been somewhat inconclusive (Douglass et al. 1996, Mills et al. 1997, Boone et al. 1998, Douglass et al. 2001), field studies suggest that mechanisms of disease transfer among deer mice include grooming, biting and wounding associated with territoriality and intraspecific competition, and communal nesting; the frequency of such interactions should increase with population density. In addition, hantavirus infection has not been found to reduce the fertility or survivorship of reservoir hosts, so populations can maintain high levels of infection without associated mortality (Mills et al. 1997, Boone et al. 1998, Mills et al. 1999, Botten et al. 2000).

Studies comparing HPS case households with control (non-HPS) households found that rodent population density was significantly higher where

HPS cases occurred (Childs et al. 1995, Zeitz et al. 1995), and a bimodal spring-fall pattern of HPS onset in human populations has been observed (Khan and Young 2001). These climax points correspond, respectively, to observed trends in SNV reservoir species for springtime peaks in antibody prevalence and fall peaks in population abundance (Abbott et al. 1999, Mills et al. 1999, Kuenzi et al. 2000, Douglass et al. 2001, Langlois et al. 2001) (Figure 3.1). Antibody prevalence is likely high in the spring because the social interactions that occur during overwintering facilitate spread of the virus from infected to uninfected individuals. Fall peaks in population occur as the result of successful reproductive periods (Mills et al. 1999, Root et al. 1999, Douglass et al. 2001, Ostfeld and Holt 2004). The pattern in onset of human disease suggests that disease risk is significantly influenced by both the total number of animals extant in a region (density), and the proportion of infected individuals (seroprevalence) within a given reservoir population. Because humans are predominantly exposed to HPS in buildings, predicting the timing of deer mouse ingress to structures will significantly further efforts to reduce disease burdens in human populations.

An additional parameter, reservoir population dispersal, may affect risk of disease in human populations. Dispersal, the movement of individuals between habitat areas, increases the density of reservoir animals in specific areas, and amplifies overall seroprevalence by increasing the frequency of encounters between infected and susceptible animals (Root et al. 1999, Langlois et al. 2001). Under normal conditions deer mice tend to move within home ranges of

about 0.27 to 2.24 acres (0.11 to 0.91 hectares), with differences in range size attributed to variability in food supply, seasonal and weather, age and sex, and population density (Stickel 1968). However, for reasons including resource limitations, habitat fragmentation and disturbance, presence of empty niches, and social pressure (Fairbairn 1978, Diffendorfer et al. 1995, Root et al. 1999, Langlois et al. 2001, Mackelsprang et al. 2001), deer mice may disperse from their home ranges. Dispersal distances vary from less than 150 meters to 1220 meters (Stickel 1968, Langlois et al. 2001). Fairbarin (1978) observed that the number of dispersing deer mice was linearly related to density of source populations, and that rate of dispersal was correlated with the rate of population increase. Type and area of habitat patches present on the landscape (landscape composition) and the spatial relationships among patches (landscape configuration) have also been implicated in small mammal dispersal, and may influence the prevalence of SNV in reservoir populations (Diffendorfer et al. 1995, Langlois et al. 2001, Mackelsprang et al. 2001). Dispersal from sylvan to peridomestic settings commonly occurs during fall and winter, in the absence of rodent-proofing measures in and around homes and outbuildings (Glass et al. 1997)

A landscape productivity model may account for *P. maniculatus* density, dispersal, and seroprevalence. Previous studies have demonstrated that rodent populations can increase under conditions that favor the development of primary and secondary trophic resources (Abbott et al. 1999, Parmenter et al. 1999, Ernest et al. 2000). Steady increases in populations may stimulate dispersal of

individuals to neighboring habitats, because of growth beyond the environmental carrying capacity, ongoing habitat fragmentation, or resource limitations caused by seasonal vegetation senescence. Dispersal may result in an increase in overall seroprevalence within populations in the dispersal region, because dispersing mice tend to be dominant males who have been shown to be the main population reservoirs of SNV (Fairbairn 1978, Kuenzi et al. 2000) (Figure 3.2). To create a model that accounts for the effects of density, dispersal, and seroprevalence on HPS disease risk in human populations the extrinsic, environmental triggers that regulate population density, dispersal, and seroprevalence must be identified. Thus, by characterizing aspects of landscape composition and configuration related to relevant reservoir population parameters, a model may predict both when and where HPS risk areas emerge.

Remotely sensed data may provide useful inputs for disease forecast models. Satellite data are collected at frequent, regular intervals over broad spatial scales, and subjected to rigorous quality control measures that ensure the distribution of timely, accurate products. In particular, the vegetation gross primary production (GPP) product from the Moderate Resolution Imaging Spectroradiometer (MODIS) may be useful for monitoring and modeling the effects of putative trophic cascades on reservoir populations. The MODIS GPP are available as 1-kilometer^2, composited weekly and annual vegetation productivity data. Although a variety of other remote sensors acquire vegetation data at a number of spatial and temporal scales, the MODIS is the first of its kind to offer near-real-time, highly accurate vegetation monitoring with integrated

spatially scaled bioclimatology, land cover specific process models, and carbon cycling logic (Friedl et al. 2002). I used MODIS GPP as an estimate of resource abundance at sylvan and peridomestic rodent trapping sites in Montana, and tested its utility as a predictor of rodent density, dispersal, and seroprevalence at these sites.

Data from sylvan and peridomestic rodent trapping sites in west central Montana provided the opportunity to analyze relationships among resources, rodent density, and rodent seroprevalence. This study specifically addressed interactions between rodent reservoir density and seroprevalence in relation to landscape composition (resource abundance). I conducted analyses to link monthly rodent density at the two sites with vegetation abundance, and tested whether population density and seroprevalence at sylvan sites (SMNA and SMNI, respectively) influenced density and seroprevalence at peridomestic sites (PMNA and PMNI, respectively) through the dispersal mechanisms described above (Figure 3.3). The timing and magnitude of changes in population density and seroprevalence at sylvan and peridomestic sites is important, because interactions between these populations influence HPS risk in humans.

Considering potential trophic responses of small mammal communities and interactions between rodents in sylvan and peridomestic settings I formulated and tested four hypotheses:

1. Granivorous rodents such as *P. maniculatus* are hypothesized to be mainly resource limited (Ernest et al. 2000), so fluctuations in resource availability should influence rodent population density at sylvan and peridomestic

trapping sites. In particular, increased resource abundance should stimulate population growth through increased rates of fecundity or immigration, with appropriate time lags; and decreased resource abundance should result in population decline through mortality or dispersal.

2. High reservoir population density and vegetation senescence (decrease in available resources), both of which commonly occur during the fall season, should drive individuals to disperse to surrounding areas. The dispersal direction should be from sylvan (source) toward peridomestic (sink) sites, resulting in increased population density at peridomestic sites.

3. Relative levels of infection at the sylvan and peridomestic sites should be highest in the spring following overwintering of populations. Subsequent late-season dispersal from sylvan sites may maintain high levels of infection in peridomestic settings, so seroprevalence may be higher at the peridomestic site following dispersal events from sylvan sites.

4. If complex and non-linear dynamics such as top-down influence of predators or density-dependent effects are present, these may complicate population responses to trophic cascades to the extent that relationships may be obscured.

Methods

Study sites

Data were obtained from sylvan and peridomestic longitudinal trapping sites in west central Montana (Figure 3.4). Both sites were located in Cascade County, separated by a distance of approximately 750 meters between site centerpoints. The sylvan site was a grassland habitat located at an elevation of

about 1425 meters above sea level. Rodents were live-trapped at the site for three consecutive nights per month, 12 months out of the year at a 1-hectare trapping grid consisting of 10-trap by 10-trap arrays of Sherman live-capture traps, spaced at 10 meter intervals. For a comprehensive description of trapping protocols and methods see Douglass et al. (2001). Although two additional sylvan trapping sites were located in the near vicinity they were not included in the analysis because they were separated from the peridomestic site by more than 1220 meters, the accepted maximum dispersal distance for *P. maniculatus*.

The peridomestic site was a cattle ranch consisting of homes, yards, driveways, fences, and fields; and outbuildings such as barns, workshops, and garages in a grassland matrix (Kuenzi et al. 2001). Building use was both daily and sporadic depending on the building type. Rodents were captured using Sherman live-capture traps set inside and around the perimeter of buildings (approximately 80% of traps) and in outside areas up to 150 meters away from buildings (approximately 20% of traps). Traps were set for three consecutive nights per month, 12 months per year, and trapping protocols were similar to those at the sylvan site.

Vegetation abundance

Vegetation abundance was estimated using gross primary vegetation productivity (GPP) data from the Moderate Resolution Imaging Spectroradiometer (MODIS), onboard NASA's Earth Observing System (EOS) Terra satellite. The GPP product provides an estimate of terrestrial biomass

accumulation, without subtracting costs of plant respiration that reduce the amount of carbon allocated to plant growth It is widely assumed, however, that the ratio of net primary production (NPP, the amount of light energy converted to biomass after respiration costs are accounted for) to GPP is a fairly constant ratio of 0.47 (Waring et al. 1998); GPP is therefore assumed to be an effective relative estimate of vegetation abundance .

To achieve the maximum site-level sensitivity from the MODIS GPP product I substituted bioclimatology data from an on-site, ground-based National Climatic Data Center (NCDC) weather station for the standard DAO input. The standard product MODIS GPP uses coarse-resolution 1.00° x 1.25° daily meteorology from the Data Assimilation Office (DAO) as its input bioclimatology, and although these data have been shown to work well across broad spatial scales they may cause over- or under-estimation of GPP at small spatial scales (Running et al. 2004, Zhao et al. 2005). For example, a recent analysis reported a 28% error between DAO and site-specific meteorology at 15 sites in North America (Heinsch et al. in press). In addition, I used the Mountain Climate Simulator (MT-CLIM) to estimate additional parameters used in the MOD17A2 GPP algorithm. For a complete and detailed discussion of this methodology and the MODIS GPP product refer to the Methods section in Chapter 2.

I obtained MODIS weekly GPP data in 3-kilometer x 3-kilometer (9 km^2) matrices over the areas of interest. The large footprint corrected for geolocation errors of the sensor, which may offset pixels by up to 150 meters in any direction for a given swath (Wolfe et al. 2002). For the sylvan site a 9 km^2 footprint (9

pixels) was centered over the midpoint of the 1-ha trapping grid. To improve the accuracy of the MODIS data for the site of interest I used only pixels in the footprint for which the satellite-derived land cover class, used as a variable in the MODIS GPP algorithm, corresponded to ground-reported land cover. For the sylvan site, six out of nine possible pixels were reported as grassland land cover and were retained. I used a linear fill method to convert weekly GPP to monthly estimates, representing the total amount of carbon fixed at the site each month. These data are assumed to represent a relative measure of biomass accumulation on the landscape.

For the peridomestic site I used a weighted average of the two satellite land cover types reported for the 9 km^2 footprint: grasslands (7 pixels) and croplands (2 pixels). Weighted averaging was used for this site because land cover consists of native grasslands as well as structures and disturbed and agricultural plots. The footprint was centered over the approximate midpoint of the site. As with GPP data for the sylvan site a linear fill method was used to convert from weekly to monthly GPP estimates. In addition to absolute GPP estimates the rate of increase in GPP per period (ΔGPP) was calculated for each site by dividing the GPP from the current month by GPP from the previous month (N_{t+1}/N_t).

Rodents

Rodent population abundance at the sylvan and peridomestic sites was given as the minimum number of individuals alive per trapping period (MNA), produced using the enumeration method (Chitty and Phipps 1966). Under this method the population was calculated as the sum of all animals captured during that period, corrected by the number of captures from the preceding and subsequent trapping periods. Monthly MNA data were available at the sylvan site (SMNA) from 1994 through 2004, and at the peridomestic site (PMNA) from 1997 through 2004. The rate of population increase (λ) was calculated for PMNA and SMNA as a means of quantifying effects of unit changes in variables. For $\lambda = 1$ there is no change in the size of the population from the previous period (month), for $\lambda > 1$ the population increased in size from the previous month, and for $\lambda < 1$ the population has declined.

Blood samples were collected from trapped animals and tested for antibody reactive with SNV recombinant nucleocapsid protein, using an ELISA (enzyme-linked immunosorbent assay) test (Childs et al. 1994, Kuenzi et al. 2001). The ELISA method detects infection by any of the known North American hantaviruses. The monthly number of infected rodents present per trapping period (MNI) was recorded for the sylvan (SMNI) and peridomestic (PMNI) sites, with the aim of testing for associations between MNA and MNI. Because not all animals captured at the site were subjected to serological testing the MNI statistic reflected the percent seroprevalence in the testing sample. The SMNI data were available from 1994 through 2004, and PMNI data were available from

1997 through 2004. A limited number of missing observations were excluded from the analysis.

Statistical analysis

Statistical analysis was performed in SPSS (SPSS 1999). Non-parametric methods were applied to continuous monthly data sets with non-normal distributions, and parametric tests were used for normally distributed annual data sets. Parametric tests were also used where monthly data were logarithmically transformed, as noted in the following section. These methods were used to test for differences in and relationships among variables suggested by the sylvan-peridomestic model for population dispersal and seroprevalence (Figure 3.3). Tests included the Wilcoxon-Mann-Whitney two-sample test for differences in means, used to compare MNA and MNI data between sites; Kruskal-Wallis multiple-samples tests for differences in means, used to evaluate monthly and annual variability in MNA and MNI within sites; and Spearman rank order and Pearson correlations for between- and within-site comparisons of MNA, MNI, and GPP. Pearson correlations were also applied to normal logarithmic distributions of λ_{MNA} and ΔGPP following the path diagram in Figure 3.3.

Results and Discussion

Rodent density and seroprevalence

Between 1997 and 2004 1,492 *P. maniculatus* individuals were captured at the peridomestic site, with an overall seroprevalence of 28.8%. During the

same time period and from approximately the same number of trapping nights 2,501 individuals were captured at the sylvan site, with an overall seroprevalence of 7.9 % (Table 3.1). A Wilcoxon-Mann-Whitney two-sample test for differences in means was significant for SMNA and PMNA (n=187, Z=-2.908, $p = 0.004$), and marginally non-significant for SMNI and PMNI (n=180, Z=-1.494, $p = 0.135$). Although cumulative sylvan rodent density was 40.3% higher than density of individuals at the peridomestic site, seroprevalence among mice trapped in and around buildings was 72.6% higher than those trapped at the sylvan grasslands site (Figures 3.5 and 3.6). These data suggest that although the probability of encountering *P. maniculatus* individuals is higher in native habitats, the probability of contact with an *infected* individual is substantially higher in or near outbuildings, barns, and houses. These data may help to explain observed patterns of infection in human populations, in which the majority of individuals are exposed to SNV in suburban and rural settings. Residence in structures may enable peridomestic rodents to maintain higher levels of disease than their sylvan counterparts because of increased survivorship in stable environments, frequency of encounters in enclosed habitats, stability of the virus in enclosed environments, and focality of populations.

There was an overall trend for deer mouse populations to peak in late summer and early fall and then decrease over the winter at both sites (Figure 3.7). The peak corresponded to the period of greatest biomass accumulation at both sites as estimated by the MODIS GPP (Figure 3.8), suggesting that resource availability influenced rodent population abundance as hypothesized.

The fall peaks in reservoir population density also correspond with the late-season mode in onset of HPS cases in human populations (Figure 3.1) (Mills et al. 1999). Seroprevalence at peridomestic and sylvan sites was highest during spring months, corresponding to the observed early-season mode in onset of HPS. Patterns in rodent density and seroprevalance at the two sites appear to support hypothesized interactions between population parameters and human disease onset, and help explain the timing of infection in humans.

Correlation analysis was used to test for covariance between MNA and MNI following the path diagram in Figure 3.3. At annual time scales *SMNA was strongly correlated with PMNI* (r_s = 0.769, p = 0.026) *and with PMNA* (r_s = 0.770, p = 0.025) for 1997 through 2004 (Table 3.2). At monthly time scales SMNA-PMNI and SMNA-PMNA correlations were weaker but still significant, and correlations between SMNA and SMNI, PMNA and PMNI were significant and positive (Table 3.3).

Although correlation analysis tests for interdependence in variables rather than causality, it seems likely that vectors of population density and infection originated at sylvan (source) sites and flowed toward peridomestic (sink) sites. A potential scenario suggested by the analysis is that increased sylvan population density stimulated dispersal to neighboring peridomestic habitat areas, increasing the number of individuals in those populations, and that these dispersal events served as direct mechanisms for transmitting infection between sylvan and peridomestic populations. Peridomestic populations then maintained high levels of SNV because enclosed environments facilitate continued disease

transmission through high frequency of encounters, virus stability, or other mechanisms.

Gross primary productivity (GPP)

The GPP data sets for the peridomestic (PGPP) and sylvan (SGPP) sites were nearly identical because of the high degree of spatial overlap between the MODIS site footprints. Small differences in monthly GPP were due mainly to the weighted averaging (peridomestic site) versus land cover averaging (sylvan site) methods of aggregating GPP across the footprints. General trends in GPP were for an increase in vegetation biomass beginning in March, peak accumulation in June or July, and October senescence followed by winter dormancy.

Pearson correlations indicated no significant relationships between GPP and MNA at annual time scales, and data plots showed that while PMNA and SMNA were highly variable across years (X^2 = 36.249, df = 4, $p \leq 0.0001$ and X^2 = 40.390, df = 4, $p \leq 0.0001$, respectively), PGPP and PMNA did not vary with year (X^2 = .794, df = 4, p = .939 and X^2 = .878, df = 4, p = .928, respectively) (Figure 3.8). Correlations between ΔGPP and λ_{SMNA} were significant and positive for the sylvan site, suggesting that unit changes in vegetation abundance are associated with rate of increase in reservoir populations (Table 3.3).

Linking vegetation abundance with disease risk

Predictive models for disease risk provide forecasts at fine enough time scales to allow for implementation of disease prevention measures. Monthly

data were analyzed for information on within-year population dynamics and seroprevalence that enables such predictions. At fine-scale monthly time steps there are positive and significant correlations between rodent density at the sylvan site and peridomestic population density and seroprevalence; however, correlation methods make no assumptions about interdependence of variables and do not allow for predictive model building. Because the aim of the study was to develop a method for predicting spatial and temporal HPS disease risk, interdependence must be established between relevant predictor and effect variables.

Linear regression analysis was used to develop a model to predict change in reservoir population abundance from ΔGPP. The linear equation λ_{SMNA} = 0.169(ΔGPP) -.001 explained about 12% of the variation in rodent population density (p = .008). Lagging monthly vegetation abundance by one to six months compared with rodent density did not improve the fit of the model and produced no significant correlations. Although the model explained only a small portion of the variation in $\lambda_{SMNA,}$ it provided sufficient evidence of a relationship between the two variables to warrant further investigation. From a human health perspective even the relatively weak predictive power of the model may provide a sufficient indicator of disease risk, because the costs associated with overestimating risk are lower than costs of underestimating, especially considering the high mortality rate associated with HPS.

Although monthly vegetation abundance and rodent density at the sylvan site were related, there was no significant relationship between vegetation and

rodents at the peridomestic site. Assuming that the relationship between sylvan and peridomestic population density is causal and driven by dispersal of individuals from native habitats to human structures, sylvan rodent density can be used to predict both rodent density and seroprevalence in peridomestic settings. These results suggest that a model to predict SMNA by association also accounts for PMNA and PMNI, and therefore captures population dynamics related to risk if disease in humans.

Conclusions

This study examined changes in population size and seroprevalence of hantavirus reservoir species, with the aim of developing a model to predict outbreaks of HPS in human populations. Following the hypotheses forwarded earlier in the paper, I conclude the following:

1. Fluctuations in vegetation productivity influence rodent population density at the sylvan trapping site to a limited degree, with same-month MODIS GPP as the strongest predictor of population density.

2. Significant and positive correlations exist between sylvan and peridomestic MNA at both monthly and annual time scales. Such associations are expected under conditions where population growth at sylvan sites stimulates dispersal to peridomestic sites.

3. Significant and positive correlations exist between sylvan MNA and peridomestic MNI at both monthly and annual time scales. Such associations are expected under conditions where dispersal from sylvan to peridomestic sites facilitates transmission of SNV between populations.

4. Complex and non-linear dynamics may explain why GPP is not a more powerful predictor of sylvan population density, and is not associated with changes in peridomestic populations. Alternatively, populations may be influenced by secondary food resources, microhabitat-scale landscape features, and climate controls on reproduction and survival, not detectable using the MODIS data set. Further analysis and model parameterization is required to elucidate these effects.

Suggestions for future research

Although the GPP data set used in the analysis predicted some of the population variability in sylvan rodents, a larger fraction of the variability was unaccounted for by the model. Vegetation abundance appeared to be a significant, although somewhat weak, predictor of sylvan population variability; these results suggest that resource abundance is not the dominant ecological factor influencing rodent population density, as postulated by the trophic cascade hypothesis. Additional important factors, not accounted for by the MODIS GPP data set, may include presence of secondary arthropod food resources, microhabitat-scale landscape composition and configuration, and temperature thresholds and limitations to reproduction.

The absence of significant correlations between annual or monthly peridomestic GPP and MNA suggests that density of that population is affected by landscape factors not fully accounted for by the fairly coarse 9km^2 MODIS GPP footprint. Previous research has suggested that microhabitat variables associated with peridomestic environments, including wood and trash piles, abandoned appliances and automobiles, fallen logs, and garden plots may

provide rodent harborage and focus populations (Childs et al. 1995, Glass et al. 1997). These landscape elements are not resolvable using MODIS imagery. Future models for sylvan and peridomestic populations could (1) include temperature as a separate model variable, applying appropriate time lags and thresholds associated with natality and mortality, (2) account for secondary trophic resources by developing a sub-routine that relates changes in temperature, precipitation, and vegetation to arthropod abundance, (3) characterize peridomestic microhabitats according to the presence of rodent harborage, and relate those characteristics to density and seroprevalence of reservoir rodents; and (4) integrate fine-scale ground-based information with satellite-driven vegetation estimates.

Mark-recapture studies could be incorporated into the current model framework to provide more precise hypothesis testing for associations between sylvan and peridomestic MNA and MNI. Because of the close proximity of the two study sites it is assumed that rodents move between sylvan and peridomestic habitats, but by tagging and releasing individuals for recapture both the direction and magnitude of dispersal could be fully investigated. Tracking the movement of individuals between sites can also be useful for distinguishing between population growth due to immigration versus growth due to increased reproductive activity. Such information is important for modeling the development of disease in reservoir populations, because while dispersal is associated with disease transmission, successful reproductive periods have been shown to decrease the overall population seroprevalence by increasing the

proportion of juvenile mice; these juveniles retain maternal antibodies to SNV and are protected from horizontal mechanisms of disease transmission (Mills et al. 1999, Root et al. 1999, Borucki et al. 2000).

Finally, this and other models that assess disease risk through analysis of disease reservoir populations can be applied over broad spatial scales, to determine whether there is overlap between predicted spatial and temporal dynamics of reservoir populations and recorded exposure sites for HPS. As noted previously, the consequences for human health associated with falsely identifying HPS risk areas may be less severe than those associated with failing to identify risk areas. Risk area assessments can be used to focus disease prevention efforts by targeting likely areas for HPS exposure, and educating populations in those areas about disease prevention, identification, and treatment. Refined models, as they are developed, will minimize forecast errors, and more precisely identify the timing and location of potential HPS outbreaks.

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Table 3.1 Annual density and seroprevalence of sylvan and peridomestic rodents at trapping sites in west central Montana, January 1997-December 2004.

	PERIDOMESTIC SITE				SYLVAN SITE			
YEAR	Total captures (PMNA)	Number tested	Number positive	Percent positive (PMNI)	Total captures (SMNA)	Number tested	Number positive	Percent positive (SMNI)
1997	109	97	27	27.8	242	214	33	15.4
1998	241	201	46	22.9	328	263	13	4.9
1999	271	232	26	11.2	188	136	8	5.9
2000	113	82	6	7.3	138	97	1	1.0
2001	48	41	2	4.9	124	70	0	0.0
2002	301	237	100	42.2	613	468	13	2.8
2003	294	237	110	46.4	740	615	72	11.7
2004	115	101	37	36.6	128	121	16	13.2
Overall	**1492**	**1228**	**354**	**28.8**	**2501**	**1984**	**156**	**7.9**

Table 3.2 Pearson correlations between annual GPP, MNA, and MNI. Letters in italics correspond to hypothesized path relationships, and pairs in bold are significant ($p \leq .05$). Where n = 8 data from 1997-2004 were used in the analysis, and where n = 5 data from 2000-2004 were used.

	Path	n	r_s	*P*
A	Sylvan GPP vs. sylvan MNA	5	0.210	0.734
B	Peridomestic GPP vs. peridomestic MNA	5	0.297	0.628
C	Sylvan MNA vs. sylvan MNI	8	0.152	0.720
D	Peridomestic MNA vs. peridomestic MNI	8	0.534	0.173
E	Peridomestic MNA vs sylvan MNI	8	0.031	0.942
F	**Sylvan MNA vs. peridomestic MNI**	8	**0.769**	**0.026**
G	**Sylvan MNA vs. peridomestic MNA**	8	**0.770**	**0.025**
H	Sylvan MNI vs. peridomestic MNI	8	0.593	0.121

Table 3.3 Spearman rank order and Pearson correlations between monthly GPP, MNA, and MNI. Letters in italics correspond to hypothesized path relationships, and pairs in bold are significant ($p \leq .05$). Where n > 60 data from 1997-2004 were used in the analysis, and where n < 60 data from 2000-2004 were used.

	Path	n	r_s	p
Pearson correlation				
A	**Sylvan ΔGPP vs. sylvan λMNA**	59	**0.341**	**0.008**
B	Peridomestic ΔGPP vs. peridomestic λMNA	55	0.186	0.173
Spearman rank order correlation				
C	**Sylvan MNA vs. sylvan MNI**	89	**0.233**	**0.028**
D	**Peridomestic MNA vs. peridomestic MNI**	90	**0.351**	**0.001**
E	Peridomestic MNA vs sylvan MNI	84	0.067	0.545
F	**Sylvan MNA vs. peridomestic MNI**	95	**0.334**	**0.001**
G	**Sylvan MNA vs. peridomestic MNA**	91	**0.652**	**≤0001**
H	**Sylvan MNI vs. peridomestic MNI**	88	**0.369**	**≤0001**

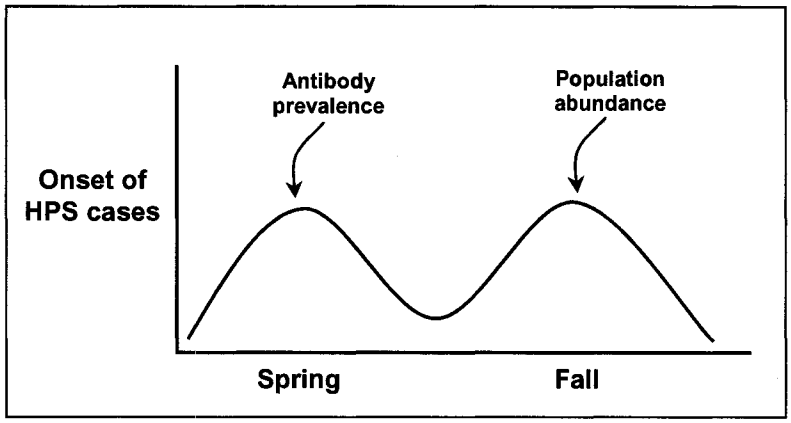

Figure 3.1 Observed trends in onset of HPS cases, where springtime onset corresponds to high levels of SNV antibody prevalence and fall onset corresponds to peaks in population abundance in hantavirus reservoir species.

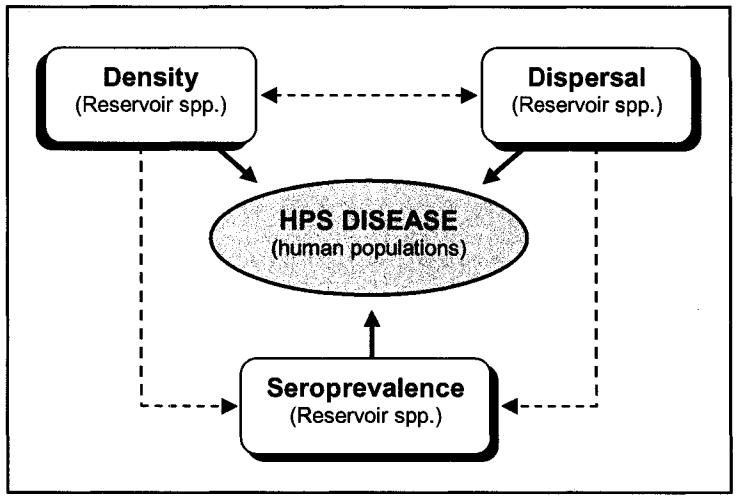

Figure 3.2 Proposed relationships between rodent reservoir population parameters density, dispersal, and seroprevalence, such that increased population density in source habitats facilitates spread of disease within the population and stimulates dispersal to neighboring regions, increasing both density and seroprevalence of those sink habitats. Consequences for human populations are increased probability of contact with infected rodents and HPS infection.

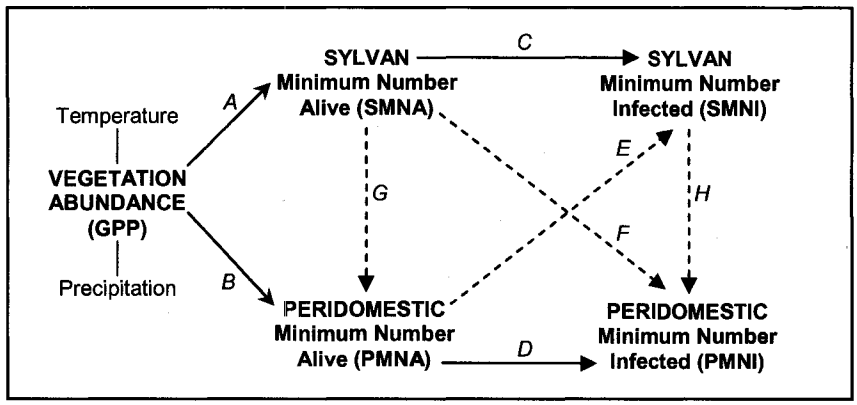

Figure 3.3 Path diagram of proposed relationships between vegetation abundance (GPP) and sylvan and peridomestic *P. maniculatus* populations. The model accounts for the role of resource abundance as a factor in promoting increased population density of sylvan and peridomestic rodents (paths A and B); within- and between-population relationships between density (MNA) and seroprevalence (MNI) (paths C, D, E, and F); and between-site associations between MNA and MNI (paths G and H). Solid arrows denote within-site relationships and dashed arrows are between-site relationships.

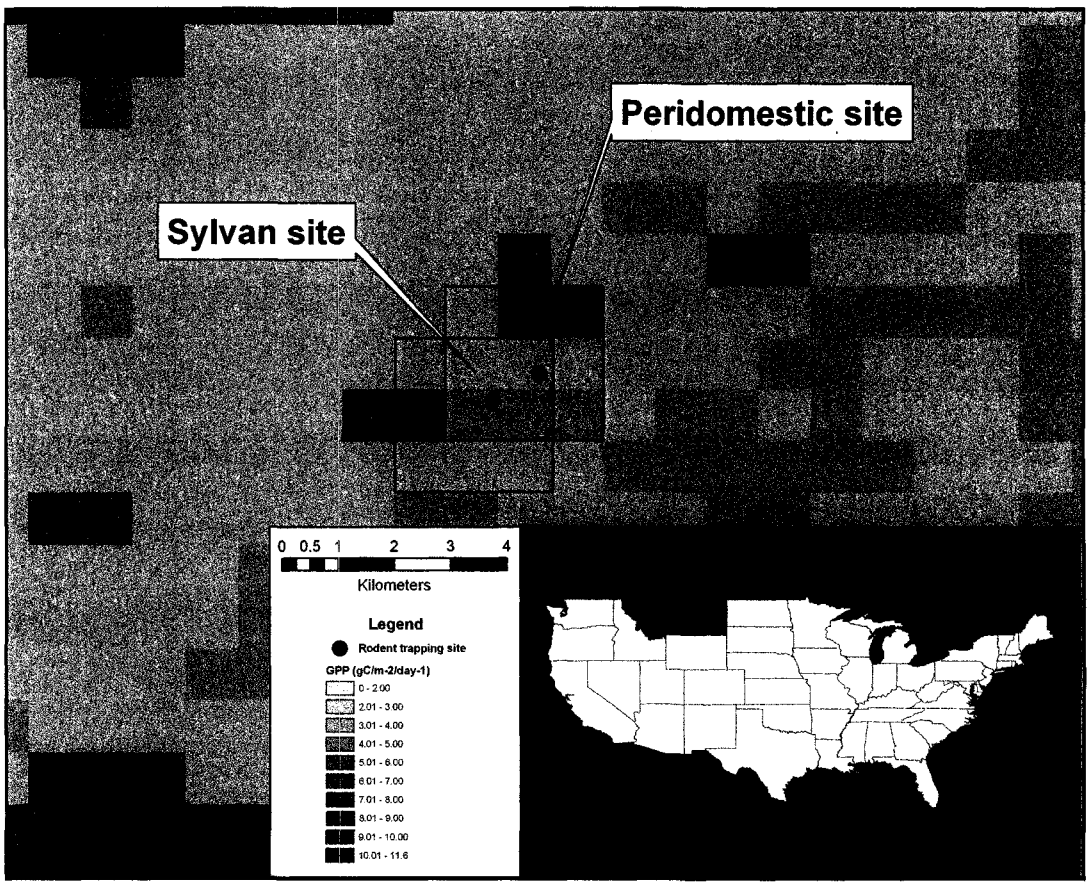

Figure 3.4 Study area showing location of peridomestic and sylvan study sites in west central Montana. Shaded background is MODIS GPP data from June 18, 2002; each square is a 1-km^2 pixel. Overlapping boxes delineate the 9-km^2 footprints over each trapping site for which MODIS data were extracted.

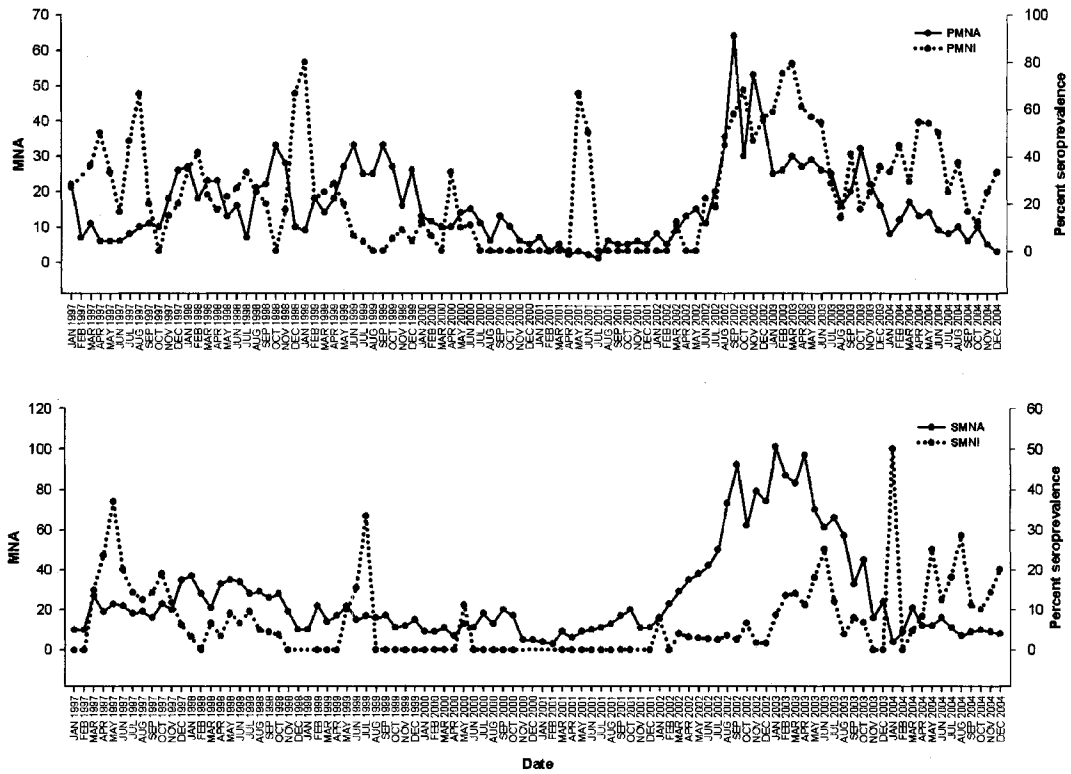

Figure 3.5 Within-site, monthly comparison of sylvan and periodomestic population density and percent seroprevalance, 1997-2004. Missing data values are months for which rodents were not trapped or blood samples were not collected from trapped animals.

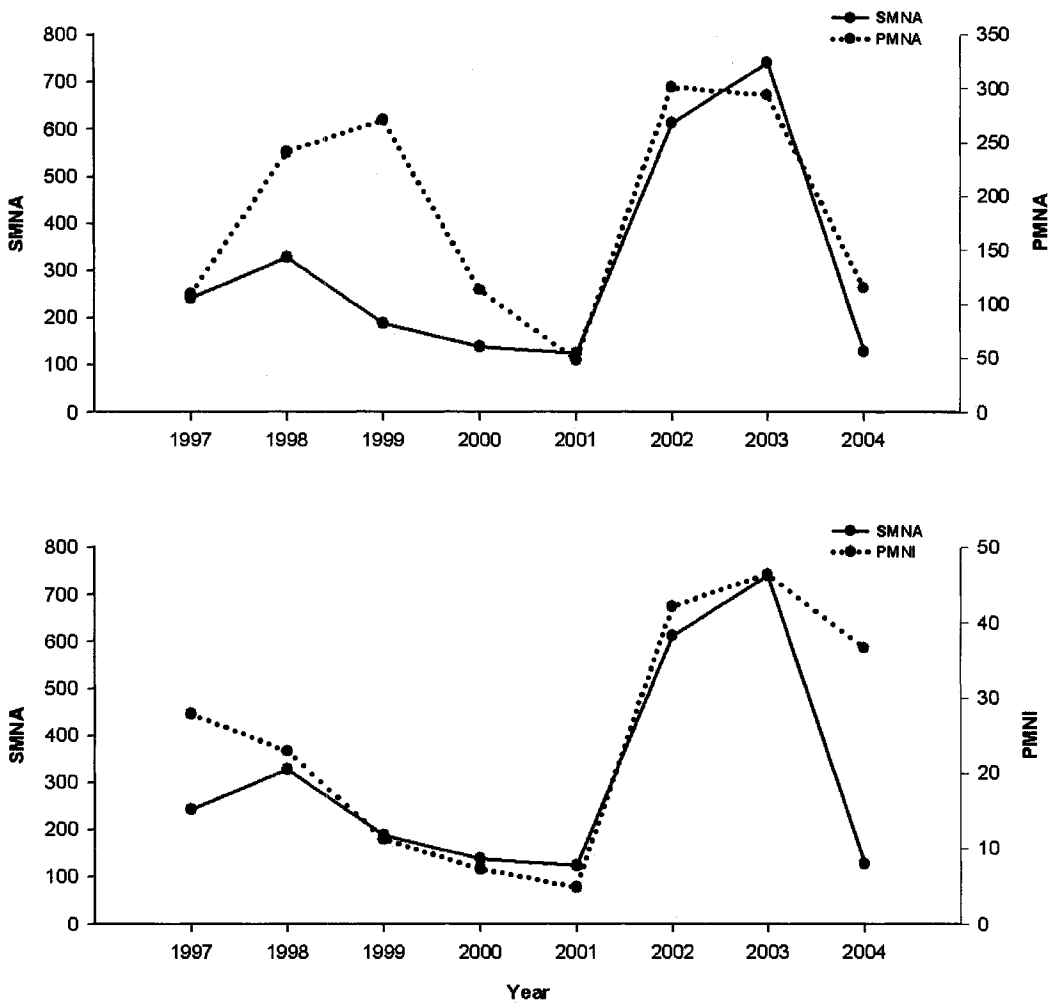

Figure 3.6 Within-site, annual comparison of sylvan and periodomestic population density and percent seroprevalance, 1997-2004. Patterns in these parameters help explain the predominant (peridomestic) location of HPS exposure in human populations

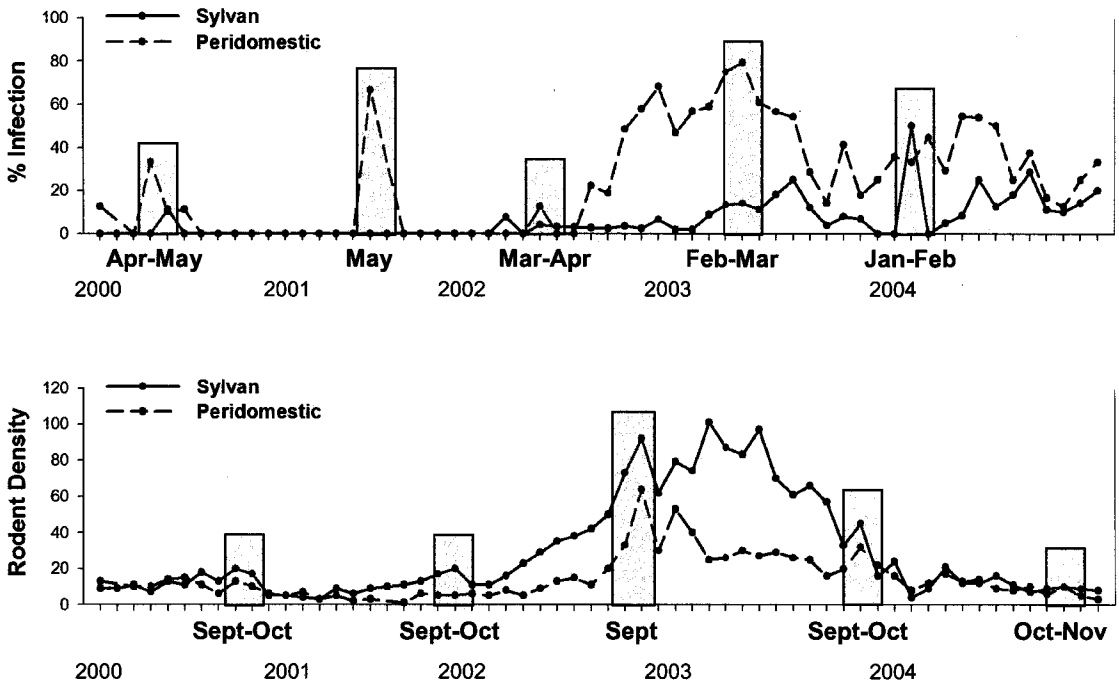

Figure 3.7 Between-site, monthly comparison of sylvan and peridomestic rodent density and percent seroprevalence, 2000-2004. Patterns in these parameters help explain the predominant (spring and fall) timing of HPS infection in human populations.

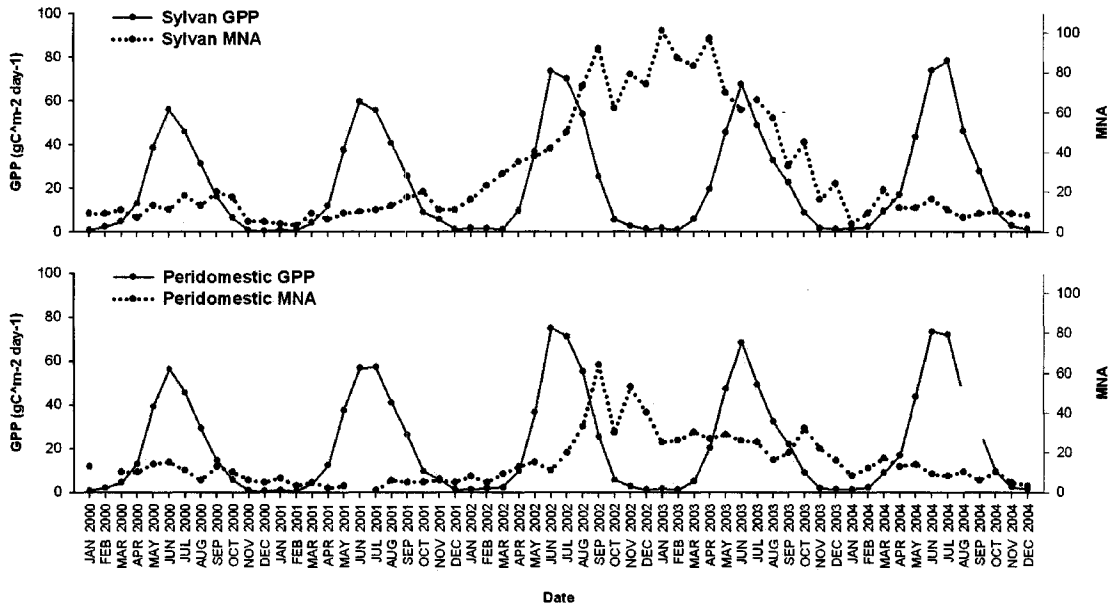

Figure 3.8 Monthly MODIS GPP over sylvan and peridomestic study sites, 2000-2004, with sylvan and peridomestic rodent abundance.

CHAPTER 4

ECOLOGICAL FOOTPRINT ANALYSIS AS A TOOL FOR ENVIRONMENTAL EDUCATION

Abstract

Ecological footprint (EF) analysis calculates the energy and resource needs of a population in terms of the land and water area required to sustain that population (Wackernagel and Rees 1996, Ferguson 2002, Wackernagel et al. 2002). This paper provides background information on ecological footprinting, especially as it relates to environmental education; curriculum ideas for teaching about environmental sustainability and resource use; and a classroom tool for calculating students' ecological footprints. Humanity's use of Earth's resources is not fixed in space or time; resource needs vary within and among countries, and as our global population grows there will be fewer available resources to support billions more people. Ecological footprint calculators such as the one presented here can be used as a hands-on method for exploring the connections among resource consumption, environmental sustainability, and global ecosystem processes.

Introduction

The past 100 years have been a time of unprecedented anthropogenic environmental changes in North America. These include dramatic expansion of urban and suburban areas and roadways, conversion of much of the continent's native prairie into cropland, impacts from extractive industries such as mining and timber harvesting, increasing use of ground and surface waters for agriculture and municipalities, and reduction in air quality resulting from fuel emissions. Urban populations have also grown increasingly dependent on importation of goods (food, clothing, building materials, automobiles, fuel, and sometimes water) from domestic and international sources, reducing the self-sufficiency of individuals, communities, and nations. As the Earth's population increases its inhabitants will place even greater demands on renewable and non-renewable resources. Estimations and projections suggest that the global population has increased from 2.5 billion people in 1950 to 6.1 billion in 2000, and may reach 8.9 billion by 2050 (United Nations 2004) (Figure 4.1). The global community is challenged now, and will continue to struggle, to balance human needs against those of other organisms.

Ecological footprint (EF) analysis is a quantitative method for assessing humanity's impact on the environment. Ecological footprint analysis incorporates biology, earth science, economics, and geography into a measurement tool that addresses the ways in which our levels of resource consumption affect Earth's abiotic and biotic resources, and influence global sustainability. The EF method is used to address such key questions as: What is the carrying capacity of the

planet? Are we living within it? What is the relationship among population, the environment, and sustainability? How can we live well, while reducing our impact on the environment? Within the United States most children and adults have heard or read about some aspect of environmental sustainability, perhaps related to recycling, improved automotive fuel efficiency, or monitoring of water and air quality. Ecological footprinting brings many of the diverse elements of sustainability together - people, land, water, and air - and facilitates improved understanding of the Earth as a complex system. Residents of the United States have an especially compelling reason to evaluate their resource use, because the U.S. per capita footprint is the largest in the world (Wackernagel et al. 1997).

This paper describes ecological footprint analysis as a tool for ecology education in upper elementary and middle school grades. Although a number of science and policy research papers exist based on this and related concepts (Hall and Clover 1997, Wackernagel and Yount 2000, Ferguson 2002, Sanderson et al. 2002, Wackernagel et al. 2002, DeFries et al. 2004, Imhoff et al. 2004), very few papers explicitly address the role of EF analysis in education or provide an education framework for teachers (Venetoulis 2001, Camill 2002, Todd 2003, Schumaker-Chadde et al. 2004). As increasing emphasis is placed on issues of global concern including declining natural resources, population pressure, urbanization and land cover change, and increasing atmospheric CO_2 and associated climate trends, the understanding of human contributions to these processes is a timely lesson for tomorrow's environmental stewards.

The EF concept provides a powerful tool for helping students understand the relationships between resource consumption and ecological sustainability. Through EF analysis students can explore such topics as community planning, resource conservation, global change, landscape ecology, energy balance, food webs, and carrying capacity. Curricula built around EF analysis can be used to meet national science content standards for scientific inquiry and investigation, life science, science and technology, and science in social perspectives, enabling teachers to incorporate ecology topics into their teaching schedule while still meeting national guidelines and education requirements.

Ecological footprint calculators can help students understand human contributions to global change, and effects of those changes on global ecosystem processes. The EF tool provides a method for objectively evaluating resource-related issues, and integrates math, social studies, geography, and ecology into science teaching in an authentic and enriching manner. Helping students understand their resource use and its relationship to ecological sustainability at local, regional, and global scales may encourage innovation of alternative, more ecologically sustainable practices and ultimately reduce the flux of energy into and waste out of households, schoolyards, and communities.

The following sections of this paper include background on EF concepts, two take-home activities for students that provide a hands-on introduction to EF methods (Appendix A), and an ecological footprint calculator designed specifically for use with upper elementary and middle school students (Appendix B). I provide information on how and where ecological footprinting activities tie in

with national science education standards, a list of resources related to ecological footprint analysis and sustainability that may supply additional teaching material, and a glossary of relevant terms. Whereas existing methods for calculating ecological footprints include web-based forms and complex spreadsheets, both of which may be difficult to use as teaching tools for younger audiences, the footprint calculator presented here is designed as an age-appropriate, paper-based instrument. By providing a classroom-ready ecological footprint calculator, along with background information and related teaching materials, I hope to address potential barriers to incorporating EF analysis into science education, and encourage teachers to explore the topic with their students.

What is ecological footprint analysis?

Ecological footprint analysis is used to calculate the energy and resource needs of individuals, populations, or regions in terms of the corresponding total land and water area required to meet those needs (Wackernagel and Rees 1996, Ferguson 2002, Wackernagel et al. 2002) (Figure 4.2). Ecological footprints represent the inverse of carrying capacity; whereas carrying capacity reflects the maximum number of individuals of a given species that a site can support, an ecological footprint calculates the size of the site required to support a human population of a given size (Camill, 2002). The average per-person ecological footprint in the United States is about 25 acres (Wackernagel et al. 1999), suggesting that in most communities human consumption exceeds the supply of

local natural capital, resulting in the necessary importation of goods and exportation of waste products.

The ecological footprint of a given individual, community, region, or nation is not fixed in time, but can be reduced through implementation of more sustainable resource use and waste production practices. As with human demand, nature's supply of resources varies through time and is influenced by changes in land use (urbanization, deforestation), climate (drought), and natural disasters (flooding, forest fires). These changes underscore the need for adoption of more sustainable practices, because they reduce the **supply** of available biologically productive land, a loss that must be countered by a reduction in **demand** to avoid "ecological overshoot" (Wackernagel et al. 2002). A number of studies have estimated that although the total human population accounts for about 0.5% of the biomass of heterotrophic organisms on Earth, humans appropriate as much as 39% of the total food energy available on land (Vitousek et al. 1986, Rojstaczer et al. 2001, Imhoff et al. 2004). A recent analysis comparing humanity's demand to the supply of natural capital demonstrates that between 1961 and 1999 our use of Earth's resources increased from 70% to 120%, indicating that we have exceeded the global carrying capacity of our planet (Wackernagel et al. 2002) (Figure 4.3). Add to this scenario predictions for a global population of 8.9 million by A.D. 2050, and we are confronted with the possibility that our current appropriation of Earth's natural capital is likely to have catastrophic effects on global ecosystem processes in the decades to come. The good news is that ecological footprint

analysis provides both the diagnosis and the cure for ecological overshoot, and can be used as a compass for directing our efforts toward global sustainability.

The EF concept was widely introduced in 1996 in the book *Our Ecological Footprint: Reducing Human Impact on the Earth* (Wackernagel and Rees 1996), in which the authors describe and quantify the impact of individuals on global ecological space in terms of the flux of resources into and waste out of communities. The authors envisioned EF analysis as a planning tool useful for exploring relationships between resource use and ecological sustainability. The original EF concept was also suggested as a method to "translate sustainability concerns into public action," because built into its metrics are solutions for reducing ecological footprints at multiple scales, from individual to community to national. By design EF calculators allow users to evaluate the impact of their personal resource consumption on global sustainability, and iteratively modify a set of behaviors to reduce or increase their ecological footprint.

Ecological footprints are calculated by estimating the amount of land area needed to support an individual's consumption of resources within five main categories: food, housing, transportation, consumer goods, and services (Wackernagel and Rees 1996). Simple mathematical equations are used to quantify resource consumption in terms of the total land area required to produce those goods and services consumed, including energy land (for fossil fuel production), consumed land (urban areas), used land (gardens, cropland, pasture, and managed forests), and limited availability land (non-managed forests and non-productive land such as ice caps or deserts). Because these

land area types are not uniformly distributed across the landscape, ecological footprints typically encompass a far greater patch of land than the area immediately surrounding a particular city or region. Translated into simple terms, this means that most of us depend on goods and services that come from outside the boundaries of the communities in which we live (are imported), and the size of our ecological footprint proportionally reflects the degree to which we rely on these non-local goods and services. Ecological footprints differ significantly by country, from 1.25 acres per person in Bangladesh to 25.75 acres per person in the United States (Wackernagel et al. 1997) (Table 4.1).

Ecological footprint calculators use four basic equations to estimate individual and population footprints. They are:

(1) c = total consumption/population size

where c is the average annual individual consumption of specific goods and services, measured in kilograms per capita and population size is the number of persons living within the community, region, or country of interest. Aggregate regional or national data on energy, food, and forest products production and consumption and census or other demographic data are used to parameterize this initial equation.

(2) $aa_i = c_i/p_i$

where aa is an estimation of the land area appropriated per capita for the production of each major consumption item (i), and p is the average annual productivity or yield of that land area expressed in kilograms/hectare.

$$(3) \quad ef = \Sigma\, aa_i$$

$$i = 1 \text{ to } n$$

where ef is the individual or per capita ecological footprint and $\Sigma\, aa_i$ is the summation of all ecosystem areas appropriated by that individual's annual consumption of goods and services.

$$(4) \quad EF_{population} = N(ef)$$

where N is the population size within the city, region, or country of interest.

In simple terms, an individual's consumption of goods and services is computed as a fraction of the population total consumption within a region of interest, translated into a spatial accounting of the amount of land area required to support that individual's consumption at an annual time step. This mass-to-area translation is calculated separately for various classes or categories of goods and services, and a final summation estimates the total land area or resource basin an individual requires for all of his/her resource needs (consumed food; fossil fuels used in transportation, food processing, and heating; waste disposal). To calculate the ecological footprint for a family, school, or community we multiply an individual's EF estimate by the size of the population of interest. This final computation assumes that all individuals within the population of interest share similar lifestyles in terms of resource consumption and waste production.

Ecological footprint calculators are available via the Internet and typically include questions related to food consumption, waste production, transportation, and housing (Redefining Progress 2002). Examples of such questions are:

What is the size of your home? How much of the food that you eat is locally grown, unprocessed and in-season? On average, how far do you go by car each week, as a driver or passenger? Activities that emphasize conservation of resources (i.e. use of public transportation and carpooling) and favor use of locally grown and processed goods result in a smaller calculated footprint, because less land area is required to offset resource consumption and waste production. By acquiring an understanding of the quantitative underpinnings of EF analysis teachers can escape the black box effect of canned web-based calculators, and provide students with a more content-rich approach to studying ecological sustainability.

Most available EF calculators are not straightforward enough to use in upper elementary and middle school classrooms because the metrics used to calculate the student's ecological footprint are expressed using wording that is too complex, or because EF calculations rely on information that is not readily available to the students. Many EF matrices are used as part of college curricula (Venetoulis 2001, Camill 2002), and require students to strictly monitor resource-related behaviors for periods of two weeks to a month. Some web-based EF calculators provide on-the-spot estimates but contain language that is not scaled to the comprehension level of most young students.

To address the problems with existing methods I developed an ecological footprint calculator specifically designed for younger students. This instrument uses a fairly standard set of questions for its calculations (Redefining Progress 2002) but has modified scoring metrics, structure, and language. I also

developed two take-home activities that give students hands-on experience with evaluating their use of resources, and effects of these practices on global sustainability. I suggest that teachers direct students to complete these activities at home before introducing the ecological footprint calculator in the classroom, because the activities are designed to engage student interest and investment in EF concepts. Exploration of global sustainability, ecosystem processes, and resource consumption needs not be confined to the activities presented here. The following sections present curriculum ideas, a list of relevant resources, and suggestions for ways in which ecological footprint analysis can be used to meet national standards for science content, that may be useful for teachers who wish to integrate EF analysis with existing curricula.

Implementing ecological footprint analysis in the classroom

In an education context the ecological footprint concept is a useful tool for helping students to visualize the global natural resource base required to support individuals, families, and communities. Through EF analysis students can calculate their resource needs, compare these footprints with national and global average ecological footprints, and identify and implement practices and programs at the household, school and community levels to reduce dependence on non-sustainable goods and services. Ecological footprint analysis allows students to engage in an active, authentic learning process through which they are made aware of their contributions to the global ecological balance, and their ability to define and enact changes to improve our planet's environment. Critical

ecological issues related to EF analysis include global warming, habitat fragmentation, and air and water quality, because the human appropriation of natural resources results in reduced and/or poorer quality resources for other organisms and natural communities. Other related ecology topics include food webs, ecosystem interactions, carrying capacity, and energy balance; teachers can effectively draw analogy among our requirements for food, housing, transportation, goods and services as expressed in the ecological footprint concept, and similar requirements in natural systems.

To introduce ideas related to resource consumption and sustainability, ask students to list their basic needs. For humans as well as most terrestrial organisms, these are air, food, shelter, and water. What other needs do students have that consume resources? Are these resources finite or infinite, renewable or non-renewable? Although many students understand the fuel costs of automobiles, they may not be aware of associated mining and manufacturing costs. Conversely, students probably have an understanding of the land costs associated with growing grain crops used to produce cereal and bread products, but they may not account for water and fertilizer used in the growing process, or fuel costs of transporting crops from fields to manufacturing plants to markets. Concept maps can be used to help students understand the relationships between human needs and ecosystem goods and services. As mentioned above, food production requires the input of many hundreds of resources including soil, water, microorganisms, atmospheric gases, plant material, metals used to make machines to harvest and process food, petroleum products to drive

those machines, and trees to absorb carbon emissions. Although not all system inputs can be easily identified, major requirements can be accounted for using an illustrated concept map. Using this method students develop a flowchart diagram for a particular food they eat, that shows the resource inputs required to produce and deliver that food item from farm to table. Rather than limit these diagrams to obvious primary inputs to the system (e.g. water, fuel, grass) students should consider secondary inputs such as those listed above.

One goal of ecological footprint analysis is to emphasize direct and indirect resource costs associated with our lifestyles, some of which we may not realize or may take for granted. Most of us rely to some degree on dry goods, food products, and energy resources that are imported, either from different regions of the United States or from other countries. In addition to the resource costs of growing, manufacturing, and extracting these products there are transportation costs associated with their importation. Similarly we are profoundly reliant on non-renewable energy resources (fossil fuels) to support our lifestyles, but may not be aware of some of the ecological implications of this dependence. The two take-home activities in Appendix A help students to evaluate the monetary, energy, and ecological costs inherent in typical American households, including use of inefficient incandescent bulbs and reliance on imported clothing and food items. After completing these activities students should have a better understanding of their personal contribution to global sustainability, be able to suggest some ways to reduce their resource

consumption, and have the foundation knowledge required to understand and implement ecological footprint analysis.

The EF calculator in Appendix B provides students with an estimate of the amount of land area required to offset their use of food, housing, transportation, and consumer goods and services, and to account for waste production. The EF calculator returns the number of global acres needed, plus a calculation for the "number of Earths" necessary to support the student's lifestyle. The resource costs associated with the typical American lifestyle have reached global overshoot, but are offset by practices in less developed nations, where individuals typically use far fewer resources.

Teachers are encouraged to help students understand and implement mechanisms for reducing resource consumption. Students can use the EF calculator to make predictions about which lifestyle choices result in smaller or larger footprints, and iteratively test their predictions by modifying their quiz answers. Some lifestyle changes may be relatively easy to make, and some may be unreasonable - there are often inherent tradeoffs between meeting human needs for goods and services and achieving goals for ecological sustainability, including economic, social, and efficiency costs associated with reducing demand on natural capital (DeFries et al. 2004).

A place-based approach to teaching about resource use and its relationship to ecosystems will provide students with a meaningful context for understanding EF concepts. Place-based approaches focus on local environmental and resource management issues (e.g. noxious weed invasion,

urban expansion, mining, logging, or water quality and availability). Because many of these issues are widely debated in popular media and local and state government forums, students may already possess useful background knowledge of and/or direct experience with relevant ecosystem components. The issues mentioned above influence regional sustainability in different ways: through reduction of available "useful land," decreased landscape productivity, and through removal or contamination of renewable and non-renewable resources. As ecological degradation progresses through time and the amount of biologically productive land within a region decreases, ecological sustainability depends on implementation of resource-conserving strategies that reduce the ecological footprint of populations within that region. The ecological footprint calculator can be used to focus attention on the relationships between local ecological issues and resource conservation; in effect, to develop a conceptual understanding of ecology as a system in which flows of energy and waste exist at multiple scales and affect and are affected by actions at each of these scales.

Explaining resource sustainability and consumption in a familiar context gives students the tools and understanding necessary for implementing practices that favor sustainability and reduce ecological footprints at multiple scales. As part of the lesson students can be asked to brainstorm things they can do at home, school, or within the community to limit resource consumption, and implement those changes over a period of time. Several examples of student-driven conservation and sustainability programs exist in the literature, and provide good models for teachers interested in implementing similar programs

(Grant and Littlejohn 2001b, 2001a, Dunn Foundation 2002, Michigan State University Extension 2002, Chadde et al. 2004).

Additional information, lesson plans, and curricula related to ecological footprints and environmental sustainability are listed in the Resources section of this paper. There are a growing number of organizations devoted to promoting these ideas, including:

- **Redefining Progress** (http://www.redefiningprogress.org/)
- **Earth Day Network** (http://www.earthday.net/)
- **Creative Change Educational Solutions** (http://www.creativechange.net/
- **Facing the Future** (http://www.facingthefuture.org/)

These organizations provide curriculum ideas, detailed lesson plans, and teacher training materials useful for implementing environmental education in the classroom.

Ecological footprint analysis and the national science education standards

National science education standards are designed to help students attain scientific literacy, and call for student exposure to a "rich array" of learning materials and inquiry-based learning focused on critical thinking and application of the scientific method of observation, prediction, and hypothesis testing (National Research Council 1996). Teachers can use EF analysis to teach key ecology concepts and address current issues, while still meeting national standards for science education. A review of the national science education standards shows that ecological footprint analysis clearly fits within a number of the broad content categories and can be used to teach specific skills prescribed

by the standards (Table 4.2). The content standards met through classroom implementation of the EF quiz and suggested extension ideas include science as inquiry, life science, science and technology, and science in social perspectives. Ecological footprint analysis can be used to fulfill prescribed learning goals and skills within each of the relevant content standards, for upper elementary and middle school students.

Conclusions

As tomorrow's environmental stewards, the current cohort of elementary and middle school students must obtain knowledge and skills necessary to make informed decisions, evaluate information, and think critically about issues of global concern. Ecological footprint analysis can be one useful tool for providing the foundation for an ecologically literate citizenry, who possess basic knowledge of the interconnectedness of human populations, natural resources, and natural communities that is fundamental to understanding today's environmental and ecological challenges. By participating in EF activities students can develop an awareness of their importance within the global ecology as producers and consumers, and as citizens who can make lifestyle changes to promote resource conservation and sustainability.

Population and resource use trends suggest that our demands on Earth's natural capital will increase, requiring new technological solutions, practices, and attitudes to avoid catastrophic ecological overshoot. Exploration of the ecological footprint concept gives students the ability to participate in decision-making and

cost-benefit analysis, and design strategies or programs by which they can make changes at the individual, school, or community scale. Ecological footprint analysis can be used to introduce and reinforce key concepts in ecology including energy balance, food webs, and carrying capacity; many of the same cost-benefit tradeoffs that influence our decisions are also present within natural systems, and non-human species are also subject to population pressures and resource limitations.

By addressing some of the obvious barriers to introducing ecological footprint analysis in primary and middle school classrooms I hope to encourage teachers to explore this and related concepts with their students. In particular, a place-based approach which emphasizes local environmental or ecological issues may provide a compelling context for learning, and offer an arena in which students can make lifestyle changes to promote sustainable communities. The ecological footprint quiz presented here may also encourage teachers to include ecological footprint analysis as part of their science curriculum, because it is scaled to favor younger users, is easily administered, and can be integrated into the curriculum as part of the nationally-prescribed science content.

The list of resources for teachers contained in this paper is inclusive but by no means exhaustive. Many additional curriculum units, activities, lessons, and papers related to resource sustainability and community planning exist that may provide valuable material for teachers and students, although, as mentioned, few explicitly address the use of ecological footprint calculators in the classroom. Since the introduction of the ecological footprint concept in 1996, it

has grown in application to include research in ecology, economics, public policy, and planning, community land-use and sustainability projects, environmental analysis and conservation studies, and education. Continued use of ecological footprint analysis to teach about resource sustainability and conservation promotes a community of ecologically-aware students, who will already be conversant with EF concepts when they encounter them as older students or adults. The development of lessons or curricula focused on use of ecological footprint calculators in the classroom is a critical step in establishing the effectiveness of ecological footprint analysis as a tool for environmental education.

Resources for Teachers

Web-based Ecological Footprint Calculators

- Redefining Progress *http://www.redefiningprogress.org/*
- Adventures with Bobbie Bigfoot *http://www.kidsfootprint.org/index.html*

Data sources for Ecological Footprint calculations

- Food and Agriculture Organization (FAO) of the United Nations *http://faostat.fao.org/*
- United Nations Development Program (UNDP) *http://hdr.undp.org/statistics/data/*
- World Resources Institute EarthTrends Environmental Information Portal *http://earthtrends.wri.org/*
- Worldwatch Institute *http://www.worldwatch.org/*

Supplemental information for the Ecological Footprint Quiz

- Information on green building techniques *http://www.greenhomebuilding.com/*
- EPA's Fuel Economy Guides, 2000-2006 *http://www.fueleconomy.gov/feg/FEG2000.htm*
- *Five Things Your Community Can Do To Reduce Its Ecological Footprint* *http://www.regionalprogress.org/StepstoSustainability.pdf*
- Ecological Footprints of Nations Report, 2004 *http://www.rprogress.org/newpubs/2004/footprintnations2004.pdf*
- Ecological Footprint FAQs *http://www.rprogress.org/newprojects/ecolFoot/faq/index.html#accuracy3*

Curriculum Links

- *Looks Count! Community Planning, Natural Resource Protection and the Visual Environment: An Interdisciplinary Middle School Curriculum Unit for Social Studies, Language Arts, Math, Science, and Art.* *http://wupcenter.mtu.edu/education/land_use/*
- *This Land is Your Land* by Michigan State University Extension: Land use curriculum materials designed to help students understand the importance and practice of wise land use. *http://www.msue.msu.edu/*
- Redefining Progress K-12 Lesson Plans *http://www.redefiningprogress.org/newprograms/sustIndi/education/k-12lessonplans.shtml*
- Creative Change Educational Solutions *http://www.creativechange.net/*
- Facing the Future *http://www.facingthefuture.org/*
- Earth Day Network *http://www.earthday.net/*

Glossary of terms

Abiotic – nonliving components of the environment, including light, climate, atmosphere, rocks, and minerals.

Acre - 4,840 square yards. One hectare contains 2.47 acres, or 10,000 square meters. An acre is approximately the size of an American football field, not counting its end zones.

Anthropogenic – caused by humans.

Autotrophic – an organism capable of synthesizing its own food from inorganic substances, using light or chemical energy. Green plants, algae, and certain bacteria are autotrophs.

Available biological capacity - the amount of biologically productive space that is available for human use.

Biotic – of or having to do with life or living organisms.

Carrying capacity – the maximum number of individuals that a given area can support without detrimental effects.

Ecological footprint - a measure of the amount of productive land and water an individual, city, country, or the world requires to produce all the resources it consumes and to absorb all the waste it generates, using prevailing technology.

Ecological overshoot - when human demand exceeds nature's supply at the local, national, or global scale.

Ecology – the study of the relationships between organisms and their environment.

Energy balance - the state in which the total energy intake equals total energy need.

Flux – flow.

Food chain - A succession of organisms in an ecological community that constitutes a continuation of food energy from one organism to another as each consumes a lower member and in turn is preyed upon by a higher member.

Food web - An organism that cannot synthesize its own food and is dependent on complex organic substances for nutrition.

Global warming - an increase in the near surface temperature of the Earth. Global warming has occurred in the distant past as the result of natural influences, but the term is today most often used to refer to the warming some scientists predict is occurring as a result of increased anthropogenic emissions of greenhouse gases.

Greenhouse effect - the effect of the Earth's atmosphere, due to certain gases, in trapping heat from the sun; the atmosphere acts like a greenhouse.

Greenhouse gases - gases that trap the heat of the sun in the Earth's atmosphere, producing the greenhouse effect. The two major greenhouse gases are water vapor and carbon dioxide. Lesser greenhouse gases include methane, ozone, chlorofluorocarbons, and nitrogen oxides.

Heterotrophic - an organism that cannot synthesize its own food and is dependent on complex organic substances for nutrition.

Natural capital - the stock of natural assets that yield goods and services on a continuous basis. Main functions include resource production (such as fish, timber or cereals), waste assimilation (such as CO_2 absorption or sewage decomposition) and life support services (biodiversity, water cleansing, climate stability).

Non-renewable resources – materials that exist in finite amounts and cannot be replenished, such as fossil fuels or metals.

Productivity - a measurement of biological production per acre per year. A typical indicator of biological productivity is the annual biomass accumulation of an ecosystem.

Renewable resources – materials that can be replaced through natural processes; examples are solar energy or trees.

Sink – an area in which more resources are used than are produced.

Source – an area in which more resources are produced than are used.

Sustainability – living within the carrying capacity of the Earth's life support systems.

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Table 4.1 Ecological footprints of nations in acres per capita (Data source: Wackernagel et al. 1997)

Country	Ecological Footprint	Available Capacity	Ecological Overshoot
Argentina	9.75	11.50	1.75
Australia	22.50	35.00	12.50
Austria	10.25	7.75	-2.50
Bangladesh	1.25	0.75	-0.50
Belgium	12.50	3.25	-9.25
Brazil	7.75	16.75	9.00
Canada	19.25	24.00	4.75
Chile	6.25	8.00	1.75
China	3.00	2.00	-1.00
Colombia	5.00	10.25	5.25
Costa Rica	6.25	6.25	0.00
Czech Rep	11.25	10.00	-1.25
Denmark	14.75	13.00	-1.75
Egypt	3.00	0.50	-2.50
Ethiopia	2.00	1.25	-0.75
Finland	15.00	21.50	6.50
France	10.25	10.50	0.25
Germany	13.25	4.75	-8.50
Greece	10.25	3.75	-6.50
Hong Kong	15.25	0.00	-15.25
Hungary	7.75	5.25	-2.50
Iceland	18.50	54.25	35.75
India	2.00	1.25	-0.75
Indonesia	3.50	6.50	3.00
Ireland	14.75	16.25	1.50
Israel	8.50	0.75	-7.75
Italy	10.50	3.25	-7.25
Japan	10.75	2.25	-8.50
Jordan	4.75	0.25	-4.50
Korea, Rep	8.50	1.25	-7.25
Malaysia	8.25	9.25	1.00
Mexico	6.50	3.50	-3.00
Netherlands	13.25	4.25	-9.00
New Zealand	19.00	51.00	32.00
Nigeria	3.75	1.50	-2.25
Norway	15.50	15.75	0.25
Pakistan	2.00	1.25	-0.75
Peru	4.00	19.25	15.25
Philippines	3.75	2.25	-1.50
Poland, Rep	10.25	5.00	-5.25
Portugal	9.50	7.25	-2.25
Russian Federation	15.00	9.25	-5.75
Singapore	18.00	0.25	-17.75
South Africa	8.00	3.25	-4.75
Spain	9.50	5.50	-4.00
Sweden	14.75	17.50	2.75
Switzerland	12.50	4.50	-8.00
Thailand	7.00	3.00	-4.00
Turkey	5.25	3.25	-2.00
United Kingdom	13.00	4.25	-8.75
United States	25.75	16.75	-9.00
Venezuela	9.50	6.75	-2.75
WORLD	7.00	5.25	-1.75

Table 4.2 Tie-ins between ecological footprint analysis and the National Science Education Content Standards (National Research Council 1996).

National Science Education Standard	Skills Base	Grade Level
A: SCIENCE AS INQUIRY		
Abilities necessary for scientific inquiry	Ask a question about objects, organisms, or events	K-4
	Communicate investigations and explanations	K-4
	Identify questions and concepts that guide scientific investigations	5-8
	Use technology to gather, analyze, and interpret data	5-8
	Develop descriptions, explanations, and models	5-8
	Use mathematics in all aspects of scientific inquiry	5-8
C: LIFE SCIENCE		
Characteristics of organisms	Basic needs of organisms	K-4
	Behavior of organisms and their environmental contexts	K-4
Organisms and their environments	Interdependence of organisms	K-4
	Response of organisms to environmental change	K-4
	Human dimensions of environmental change	K-4
Regulation and behavior	An organism's behavior evolves through adaptation to its environment	5-8
Populations and ecosystems	Matter, energy and organization in living systems	5-8
E: SCIENCE AND TECHNOLOGY		
Understanding about science and technology	Invention of tools and techniques to solve scientific problems	K-4
	Technological solutions have side effects, and carry costs, risks and provide benefits, and have constraints	5-8
	Perfectly designed solutions do not exist; all solutions have tradeoffs and unintended consequences	5-8
F: SCIENCE IN PERSONAL AND SOCIAL PERSPECTIVES		
Characteristics and changes in populations	Changes in population density over time and across the landscape	K-4
Types of resources	Basic characteristics of resources	K-4
	Resource limitations and conservation	K-4
Science and technology in local challenges	Effects of inventions, ideas, and ways of solving problems	K-4
Populations, resources, and environments	Causes of environmental degradation and effects of overpopulation on the environment	5-8
Natural hazards	Human activities can induce resource-related hazards	5-8
Risks and benefits	Individuals can use systemic approaches to thinking critically about risks and benefits	5-8

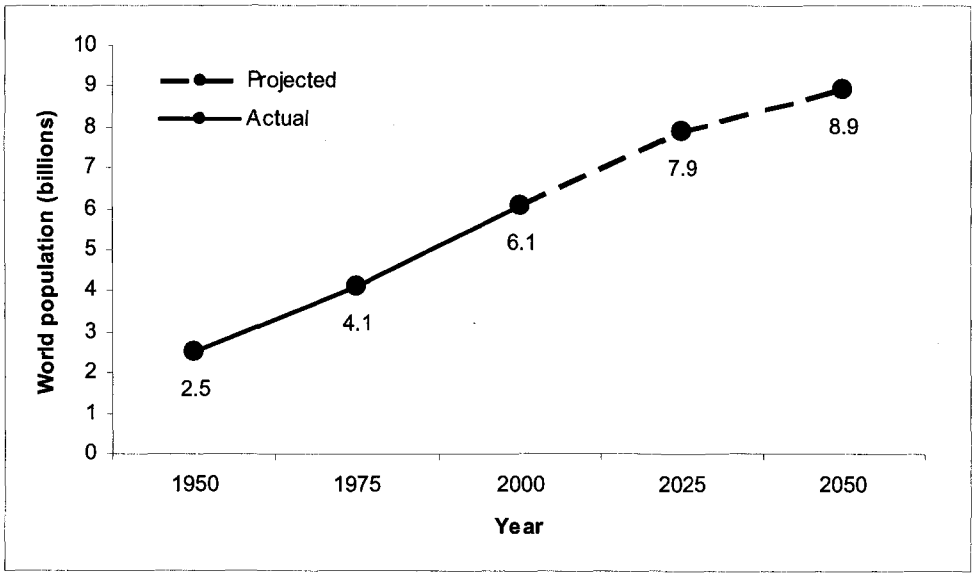


Figure 4.1 Actual (1950-2000) and projected (2000-2050) world population in billions of people (Data source: United Nations 2004).

Figure 4.2 Ecological footprint (From Zero Waste Services, http://www.zerowaste.ca/)

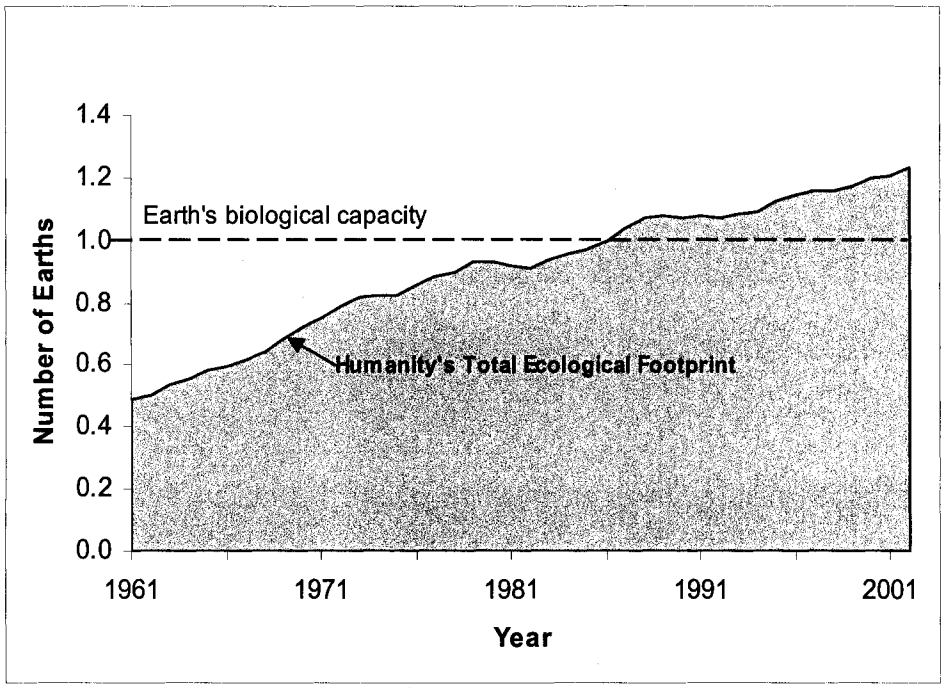
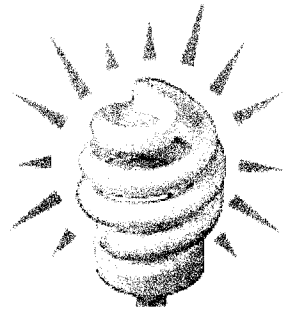


Figure 4.3 Ecological overshoot, 1961-2002. The dashed line represents the Earth's biological capacity, and the shaded region is resource use relative to that capacity, demonstrating that by 2002 global overshoot equaled about 120% of Earth's available resources. (Data source: Global Footprint Network 2005).

APPENDIX A

Change a Bulb – Save a Watt!



Did You Know?

Incandescent bulbs, the type used by most people in the light fixtures in their houses, waste considerable energy compared to **compact fluorescent** (CF) bulbs. Incandescent bulbs use about 90% of their energy making a metal element inside the bulb white-hot – this is what produces light. By comparison, CF bulbs create light by passing electricity through a gas trapped in the bulb, so much less heat energy is lost and CF bulbs are more energy efficient. The energy wasted by incandescent bulbs costs money (see the table below), creates pollution (because the electricity needed to power the bulbs often comes from pollutant sources such as coal-fired power plants, which release **greenhouse gases** into the atmosphere), and may cause harmful climate changes. Some greenhouse gases that affect global climate are carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O)[1].

The burning of **fossil fuels** for energy is thought to have increased Earth's average temperature by about 0.6 °Celsius (33 °Fahrenheit) over the past 100 years[2], and **global warming** will likely continue in the future unless we reduce the amount of greenhouse gases we put into the atmosphere Effects of increased temperatures include melting of polar ice caps and glaciers, droughts, loss of valuable coastal areas, spread of diseases, death of ocean corals, and loss of important habitat areas for plants and animals[3].

You can make a difference! Using electricity isn't wrong, but we can figure out how to use energy in smarter and more efficient ways. The average American home uses about 30 incandescent light bulbs, 3 of which burn for 5 or more hours per day. If we all replaced just 3 of these bulbs with CF bulbs, we could save as much electricity as is produced by 11 fossil-fuel fired power plants, prevent about 23 million tons of CO_2 from entering the atmosphere, and save about $1,800,000,000[4]! Complete the activities below to figure out how much electricity you use to light your house, and how much you can save by switching to energy efficient light bulbs.

What other things can you do to help make the planet a better place?

Incandescent vs. Compact Fluorescent Light Bulbs

Bulb Type	100 Watt Incandescent	23 Watt Compact Fluorescent
Purchase price	$0.75	$11.00
Life of the bulb	750 hours	10,000 hours
Number of hours burned per day	4 hours	4 hours
Number of bulbs needed	6 per 3 year period	1 per 7 year period
Total cost of bulbs	$4.50	$11.00
Lumens produced	1,690	1,500
Total cost of electricity	$35.04	$8.06
Total cost over 3 years	$39.54	$19.06

Source: Energy Information Administration, U.S. Department of Energy

[1] Energy Information Administration, U.S. Department of Energy, http://www.eia.doe.gov/
[2] Intergovernmental Panel on Climate change, http://www.ipcc.ch/
[3] Environmental Protection Agency, http://www.epa.gov/globalwarming/kids/
[4] Ban the Bulb, http://banthebulb.org

Collect Data

1. Record the number of light bulbs in each room of your house. Halogen bulbs use more energy than incandescent bulbs, and must be counted three times. If you already use compact fluorescent bulbs in some of your light fixtures, do not count these.

2. Calculate the total number of non-CF bulbs in your house by adding all the numbers in the first column of your data sheet. Calculate the total number of hours each day you use these bulbs by adding the numbers in the second column of your data sheet. Multiply these two totals together to calculate the total hours of operation for all the non-CF bulbs in your house. You will use this information later in the exercise.

	Number of bulbs in each room	**Number of hours used each day**
Living Room		
Dining Room		
Family Room		
Kitchen		
Bedrooms		
Bathrooms		
Hallways		
Basement		
Garage		
Outside		
Other		

Total number of non-CF bulbs in your house = _____

Total number of hours used each day = _____

Total hours of operation
(number of bulbs x number of hours used each day) = _____

"Watts" Your Use?

What would happen if you replaced all the incandescent or halogen light bulbs in your house with compact fluorescent (CF) bulbs? Use the questions below to figure out how much energy you would save in a year.

1. Each energy-efficient compact fluorescent bulb saves 55 watts. How many watt-hours could you save each day by changing to CF bulbs?

_____ **WATT-HOURS SAVED EACH DAY** = _____ **TOTAL HOURS USED EACH DAY** **X** **55 WATTS**

2. Your utility company measures your electricity use in kilowatt-hours (look at your utility bill). How many kilowatt-hours each day would you save by switching to CF bulbs?

_____	**KILOWATT-HOURS SAVED EACH DAY**	=	_____	**WATT-HOURS SAVED EACH DAY**	÷	**1000**

3. How many kilowatt hours would you save in a year by switching to CF bulbs?

_____	**KILOWATT-HOURS SAVED EACH YEAR**	=	_____	**KILOWATT-HOURS SAVED EACH DAY**	X	**365**

4. By using less electricity we produce less carbon dioxide (CO_2), a greenhouse gas, and every kilowatt hour you save keeps about 2 pounds of CO_2 from entering the atmosphere. How much CO_2 will you keep out of the atmosphere in a year by changing to CF bulbs?

_____	**POUNDS OF CO_2 SAVED EACH YEAR**	=	_____	**KILOWATT-HOURS SAVED EACH YEAR**	X	**2**

5. How much money will your family save in a year by switching to CF bulbs? Look on your utility bill to find the amount you pay per kilowatt-hour. The information on your bill should look something like this:

Energy Charge	3489	KWH @	0.09526	332.3

meaning that you pay 9.5¢ per kilowatt-hour. If you don't know how much your utility company charges, use the rate for Denver, 8.9¢ per kilowatt-hour.

_____	**AMOUNT OF MONEY SAVED EACH YEAR**	=	_____	**KILOWATT-HOURS SAVED EACH YEAR**	X	**COST PER KILOWATT-HOUR**

Map Your Use!

Did You Know?

Most of us rely on and use dry goods (clothing, cars, books, etc.) and food products that are **imported** (brought in from outside our region, state, or country). In addition to the resources and raw materials used to grow, process, and manufacture these products money and energy are required to import them to your local stores. Burning **fossil fuels** for energy to power the trains, airplanes, ships, and trucks that transport goods around the world releases carbon dioxide (CO_2), a **greenhouse gas**, into the atmosphere. The buildup of atmospheric CO_2 over the past 100 years has increased global average temperatures by about 0.6 °Celsius (33 °Fahrenheit)[5], causing melting of polar ice caps and glaciers, droughts, loss of valuable coastal areas, spread of diseases, death of ocean corals, and loss of important habitat areas for plants and animals[6].

You can make a difference! Buying imported food and clothing isn't wrong, but we can figure out how to use energy in smarter and more efficient ways. The average American car releases about 1 pound of CO_2 for every mile driven,[7] and larger, less-efficient vehicles (trucks, airplanes, ships) release even more CO_2. Can you think of some things you can do to reduce resource costs associated with your clothing and food needs? Complete the activities below to figure out where your food and clothing comes from, and how much CO_2 was released in transporting it to your local store.

Instructions

3. Mark the approximate location of the place where you live on the attached Clothing and Food maps.

4. Choose three pieces of clothing from your closet or dresser, and use the sewn-in tags to find out where those items were manufactured. Use the data sheet to record a description of each item (ex. "T-shirt," "jeans"), and locate and mark its place of manufacture on the Clothing map. If the tag lists more than one location (ex. "Fabric made in U.S.A., assembled in El Salvador) mark and label both locations on the map.

5. Choose three packaged food items from your pantry or refrigerator, and use the packaging to find out where those products were manufactured. Record a description of each item (ex. "cheese," "Cheerios") in the data sheet. Locate and mark its place of manufacture on the Food map.

6. Using a ruler and the scale bar underneath each map, calculate the distance from each of the marked points to the place where you live, and record that distance in the data sheet in the Distance column.

Suggested materials

- World map or atlas
- Pencil
- Ruler

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[5] Intergovernmental Panel on Climate change, http://www.ipcc.ch/
[6] Environmental Protection Agency, http://www.epa.gov/globalwarming/kids/
[7] Energy Information Administration, U.S. Department of Energy, http://www.eia.doe.gov/

Collect Data

	Item description	Distance
My Closet		

	Item description	Distance
My Kitchen		

Total clothing import distance = _____ miles

Total food import distance = _____ miles

Clothing + food import distance = _____ miles

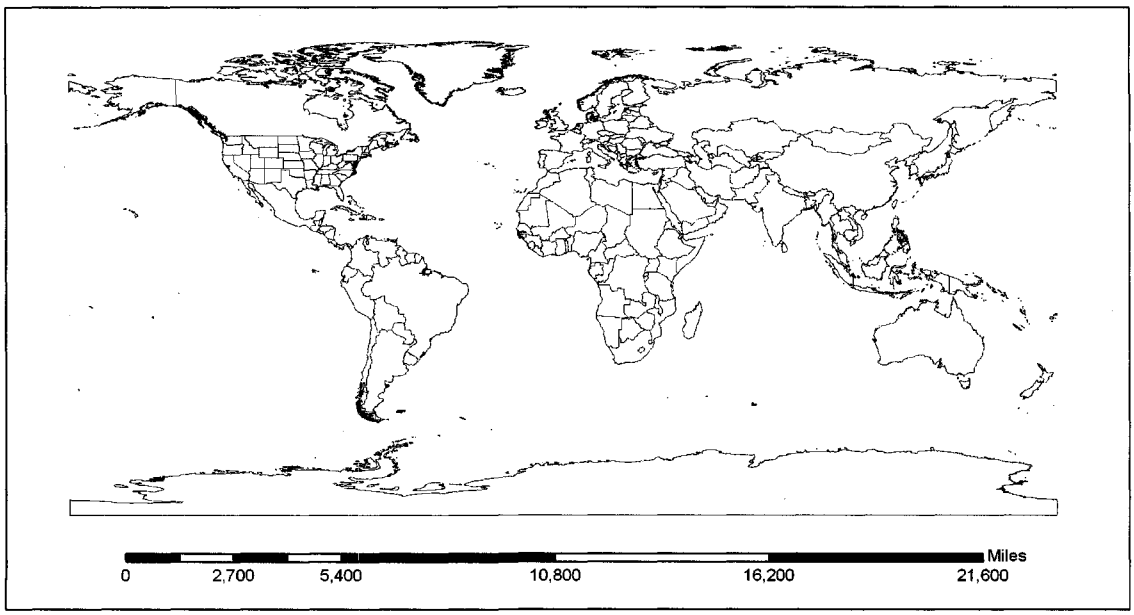
Compute Your Use

Assume that for each mile your clothing and food travel from where they were made to your local store 1 pound of CO_2 is released (this is a conservative estimate because larger vehicles release more CO_2). How many pounds of CO_2 were released in importing the clothing and food listed in your data sheet?

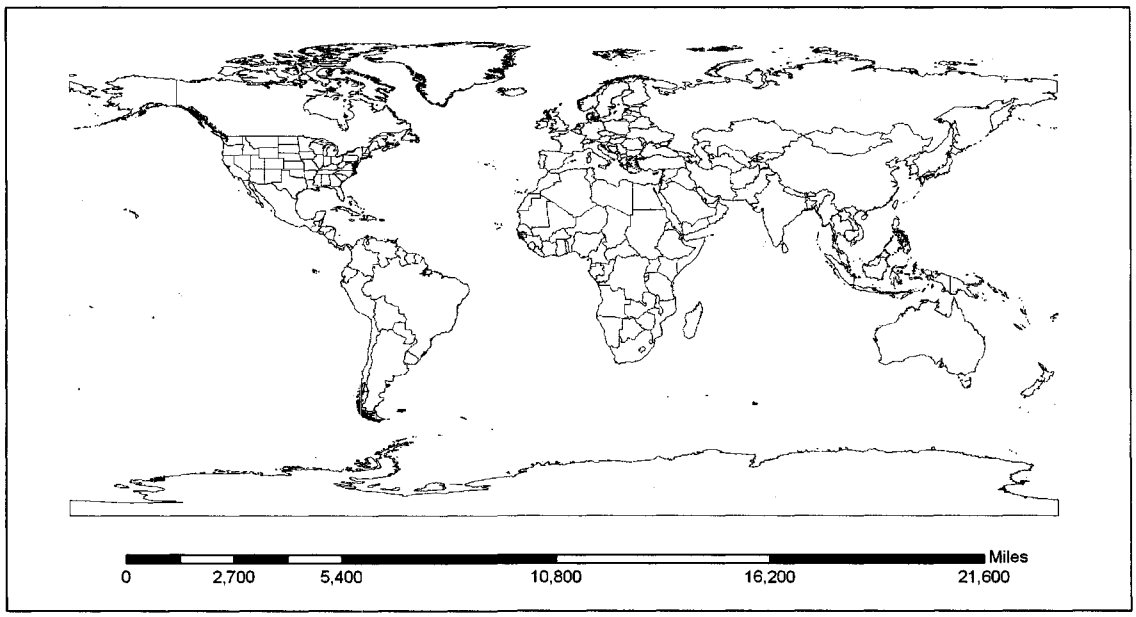
_____ **POUNDS OF CO_2 RELEASED** = _____ **TOTAL IMPORT MILES** **X** **1 POUND CO_2**

What other things can you do to help make the planet a better place?

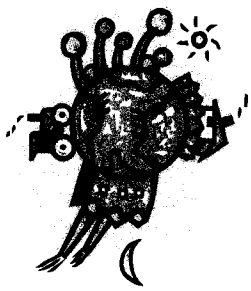
Clothing Map



Food Map



APPENDIX B



YOUR ECOLOGICAL FOOTPRINT

A QUIZ TO HELP YOU UNDERSTAND YOUR IMPACT ON THE EARTH

Have you ever wondered about the amount of resources it takes to support your lifestyle? Your lifestyle is everything about you: the food you eat, the places you shop, the house you live in, the cars you or your parents drive, and the things you throw away. This quiz estimates how much productive land and water is needed to grow your food, produce building materials, heat, and water for your house, manufacture and power your cars, and account for the trash and waste you produce. After taking this quiz you'll be able to compare the resources you use to the total available amount on this planet (in global acres), and figure out ways that you can reduce your impact on the Earth.

INSTRUCTIONS

1. For each numbered question find the answer that best describes you
2. Fill in the answer in the labeled boxes on your score sheet
3. Use the score sheet to calculate your footprint for each section (Food, Goods, Shelter, Mobility)
4. To find your total ecological footprint transfer the scores for each section into the boxes in the TOTAL ECOLOGICAL FOOTPRINT grid and calculate your total footprint using the equations provided

****Note: For some sections you will have to multiply or divide your scores by other numbers**

SUGGESTED MATERIALS

1. Pencil
2. Calculator

FOOD FOOTPRINT

1. How often do you eat animal-based foods (beef, pork, chicken, fish, eggs, milk products)?

a) **Never** (vegan)	0.46
b) **Not very often** (no meat; eggs/dairy a few times a week)	0.59
c) **Sometimes** (no meat or infrequent meat; eggs/dairy almost daily)	0.73
d) **Often** (meat once or twice a week, eggs/dairy almost daily)	0.86
e) **Very often** (meat daily, eggs/dairy daily)	1.00
f) **Almost always** (meat and eggs/dairy in almost every meal)	1.14

2. How much of your food did you, your family, or someone living near you grow or produce? Examples of locally produced foods are vegetables from your garden or a farmer's market, or locally-hunted game. If your food comes from a supermarket, chances are it's not locally grown or produced.

a) **Most or all**	0.69
b) **More than half**	0.79
c) **Half**	0.90
d) **Less than half**	1.00
e) **Almost none** (most of my food is processed or packaged)	1.10

GOODS FACTOR

3. Compared with people in your neighborhood, how much trash do you throw away?

a) Much less trash	0.75
b) About the same amount of trash	1.00
c) Much more trash	1.25

SHELTER FOOTPRINT

4. Which describes your home?

a) **Green-design home** (powered by sun or wind; made of recycled materials; energy efficient design and appliances)	0.50
b) **Multistory apartment building**	0.80
c) **Free-standing house**	1.00

5. What is the size of your home? (The average U.S. house size is 1,700 square feet.)

a) **500 square feet or smaller** (studio apartment; no bedrooms, 1 bath)	0.30
b) **500-1,000 square feet** (1 bedroom, 1 bath)	0.60
c) **1,000-1,500 square feet** (2 bedrooms, 1 bath)	0.90
d) **1,500-1,900 square feet** (2 bedrooms, 2 baths)	1.30
e) **1,900-2,500 square feet** (3 bedrooms, 2 baths)	1.50
f) **2,500 square feet or larger** (4 bedrooms, 2 baths or larger)	1.90

6. Does your house have energy efficient features (solar panels, compact fluorescent light bulbs, or EnergyStar appliances)?

a) **All energy efficient features**	0.70
b) **Some energy efficient features**	0.85
c) **No energy efficient features**	1.00

7. How many people live in your house, including you?

a) **Seven or more**	7.00
b) **Six**	6.00
c) **Five**	5.00
d) **Four**	4.00
e) **Three**	3.00
f) **Two**	2.00
g) **One**	1.00

MOBILITY FOOTPRINT

Car Travel Subtotal

8. On average, how many miles do you travel each week in a car (as a driver or a passenger)?

a) **0 miles**	0.00
b) **1 - 100 miles**	0.12
c) **101 - 200 miles**	0.55
d) **201 - 300 miles**	1.00
e) **301 - 400 miles**	1.43
f) **More than 400 miles**	1.91

9. How fuel efficient is your car? (or estimate the average fuel efficiency of the cars you ride in.)

a) **I don't travel by car**	0.00
b) **Very fuel efficient** (More than 50 mpg: hybrid gas-electric cars)	0.31
c) **Fuel efficient** (35-50 mpg: compact and sub-compact cars)	0.46
d) **Somewhat fuel efficient** (25-34 mpg: midsize cars and wagons)	0.65
e) **Not very fuel efficient** (15-24 mpg: smaller sport utility vehicles and trucks)	0.98
f) **Not fuel efficient at all** (fewer than 15 mpg: full-sized trucks, vans, and SUVs)	1.54

10. How often do you ride in a car with someone else (carpool)?

a) **I don't travel by car**	0.00
b) **Almost always**	0.50
c) **Very often** (about 75% of the time)	0.60
d) **Often** (about 50% of the time)	0.75
e) **Sometimes** (about 25% of the time)	1.00
f) **Almost never**	1.50

MOBILITY FOOTPRINT CONTINUED

Public Transit Subtotal

11. On average, how many miles do you travel on public transportation each week (bus, train, subway, or ferry)?

a) **0 miles**	0.00
b) **1 - 25 miles**	0.04
c) **26 - 75 miles**	0.15
d) **76 - 200 miles**	0.42
e) **More than 200 miles**	0.86

Air Travel Subtotal

12. About how many hours do you spend in an airplane each year?

a) **0 hours**	0.00
b) **3 hours**	0.18
c) **10 hours** (one coast-to-coast US round-trip per year)	0.60
d) **25 hours** (two or three coast-to-coast U.S. round-trips per year)	1.50
e) **100 hours** (one coast-to-coast US round-trip per month)	6.00

ECOLOGICAL FOOTPRINT SCORE SHEET

FOOD FOOTPRINT	
Your score for Question 1 (Q1)	
Your score for Question 2 (Q2)	
YOUR FOOD FOOTPRINT = Q1 x Q2 x 5.5	

GOODS FACTOR	
Your score for Question 3 (Q3)	

SHELTER FOOTPRINT	
Your score for Question 4 (Q4)	
Your score for Question 5 (Q5)	
Your score for Question 6 (Q6)	
Your score for Question 7 (Q7)	
YOUR SHELTER FOOTPRINT = Q4 x Q5 x Q6 x 13.26 /Q7	

MOBILITY FOOTPRINT		
Car Travel Subtotal	Your score for Question 8 (Q8)	
	Your score for Question 9 (Q9)	
	Your score for Question 10 (Q10)	
	YOUR CAR TRAVEL SUBTOTAL = Q8 x Q9 x Q10 x 4	
Public Transit Subtotal	Your score for Question 11 (Q11)	
Air Travel Subtotal	Your score for Question 12 (Q12)	
	YOUR MOBILITY FOOTPRINT = Car Travel + Public Transit + Air Travel Subtotals	

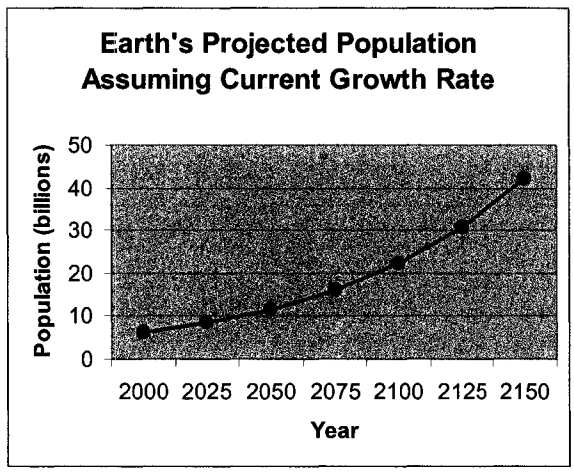
TOTAL ECOLOGICAL FOOTPRINT	
(1) FOOD FOOTPRINT	
(2) SHELTER FOOTPRINT	
(3) MOBILITY FOOTPRINT	
(4) GOODS FACTOR	
(5) SHELTER + MOBILITY: Add (2) + (3)	
(6) GOODS & SERVICES: Multiply (4) x (5) x .9	
Total Ecological Footprint = (1) + (2) + (3) + (6)	

- Your total ecological footprint is the number of global acres needed to provide for your food, housing, transportation, and to account for the amount of waste you produce.

- To calculate the number of earths needed to support your lifestyle, divide YOUR TOTAL FOOTPRINT by 4.5, the number of acres available for each person worldwide.

- The average ecological footprint in the United States is 25 acres per person. Is your footprint higher or lower than the national average?

- Because the worldwide footprint is dependent on the number of people (population) alive today, when the population increases the amount of land available for each person decreases. Look at the population graph below and predict how this will affect the number of acres of land available worldwide over time.



Data source: Redefining Progress http://www.redefining progress.org